GERARD A. MOERMAN

Empirical Studies on Asset Pricing and Banking in the Euro Area

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Empirische studies naar het prijzen van aandelen en de bankensector in het eurogebied

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Voorwoord

Dit proefschrift is een afsluiting van een periode van 5 jaar, waarin ik mij op verschillende vlakken duidelijk ontwikkeld heb. Onervaren en net afgestudeerd begon ik als 'aio' bij de vakgroep Financieel Management aan de faculteit Bedrijfskunde van de Erasmus Universiteit Rotterdam. In het begin was de richting nog niet helemaal helder, waardoor het eerste jaar meer getypeerd werd door verbreding en cursussen. Toch werd al snel duidelijk dat mijn interesse bij de financiële markten lag en dat ik graag wilde onderzoeken welke factoren bepalend zijn voor deze markten. Zoals mijn goede vriend Chris Martin altijd zegt:

> *"I was just guessing, numbers and figures, pulling the puzzles apart.*
> *Questions of science, science in progress…."*

(Coldplay, The scientist)

In dit proefschrift heb ik geprobeerd een aanzet te geven tot de oplossing van enkele vraagstukken ('puzzels') in de financiële wereld en probeer ik een bijdrage te leveren aan de wetenschappelijke 'body of knowledge'. Het is echter nog steeds 'science in progress' en dit proefschrift is dus ook zeker niet het eindpunt van mijn onderzoeken.

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Gerard Moerman
Rotterdam, april 2005

Contents

Chapter 1

Introduction

1.1 Motivation

European capital markets have changed dramatically over the last couple of years. Not only are these financial markets influenced by major global developments, but the European integration process also influences them, which is very important in defining the changing playground for investors. To start with the latter, the rate at which changes in Europe have taken place has been increasing over the most recent decades. The start of the integration process, however, had already been initiated in 1950 by the declaration of Schuman. This is discussed in more detail in section 1.2. The actual integration process for financial markets, however, has accelerated over the last two decades. A new impulse was given by the Single European Act that came into force in 1987 and formed the basis for the establishment of an internal market for goods, persons, services and capital. The introduction of the euro on January 1, 1999 provided a second boost for the European integration process. The advent of the euro eliminated the exchange rate risk within the European Monetary Union (EMU) and forced interest rates to be equal over all euro-participating countries. Additionally, as of 1999, monetary policy in Europe has been conducted by one central organization, the European Central Bank, instead of by different central banks for each member state. A very nice example of evidence of the quickly changing environment in Europe is put forward by Adjaouté and Danthine (2003), who plot the evolution of the redemption yields for several euro-area government bonds for the period 1985-2002 (Figure 1, chapter 5). For the first part of their sample a clear dispersion is noticeable among these government bond redemption yields. However, the differences are almost negligible after 1999, which is a direct consequence of the introduction of the common currency. This simple observation provides one example of the European integration process. In this thesis we focus on European stock markets by examining asset-pricing models, diversification effects and riskiness of these markets. Several chapters of the thesis investigate whether the European integration process resulted in any changes for the investors in euro area stock markets.

1.2 Introduction to the integration process in the euro area

All chapters in this thesis in some way concentrate on the stock markets in the euro area. Most of the chapters try to picture what has changed over the last decade(s) in terms of portfolio diversification, asset pricing or risk. The euro area or European Monetary Union is an especially interesting area, since the number of changes has been tremendous. The harmonization of monetary and policy rules has changed the rules of the game. This thesis shows that these changes are also reflected on asset markets in the euro area. The purpose of this chapter is to give a short historical overview of the integration process in Europe in order to provide a deeper background for the following chapters and to discuss briefly how these developments are taken into account in the several studies of this thesis.

The integration process among the European countries is not just from the recent past, but was initiated long before for both political and economical reasons. The actual historical roots of the European Union lie just after the Second World War. In order to prevent wars like these happening again, the European countries needed to come together, starting with the age-old opponents of France and Germany. This led to the "Schuman declaration" on May 9, 1950, which is considered to be the birth of the European Union as we know it now, and which is called Europe Day for this reason. The declaration proposed putting the production of coal and steel of France and Germany under a common High Authority, which was also open for other European countries to participate. Only one year later the Treaty establishing the European Coal and Steel Community (ECSC) was signed.

This treaty is the first of the four founding treaties of the European integration process. The others are the Treaty establishing the European Economic Community (EEC), the Treaty establishing the European Atomic Energy Community (Euratom) and the Treaty on the European Union. This last Treaty is also known as the Maastricht Treaty, and was signed on 7 February 1992 (becoming effective on 1 November 1993). Since the Maastricht Treaty the European Economic Community is called the European Community. Additionally, new forms of co-operation were introduced by means of this treaty, e.g. in the area of defense and “justice and home affairs”. Through this addition, a new structure was created, which is both political and economic. The addition of the intergovernmental co-operation to the existing European Community forms the structure with the so-called three “pillars”. This is the European Union (EU). Over the years, the number of member countries of the EEC or EU respectively has been increasing. The Treaty of ECSC was signed by 6 countries: Germany, Belgium, France, Italy, Luxembourg and the Netherlands. In later years other countries joined the European Economic Community: Denmark, Ireland and the United Kingdom (1973), Greece (1981), Spain and Portugal (1986) and Austria, Finland and Sweden (1995). Very recently, ten more countries have acceded to the European Union. On 1 May 2004, the Czech Republic, Estonia, Cyprus, Latvia, Lithuania, Hungary, Malta, Poland, Slovakia and Slovenia all joined the EU.

So far, the discussion mainly covers the political and economical integration process. The monetary integration process is somewhat different, though it’s history is just as long. Gros and Thygesen (1998) give an overview of the history of monetary policy in Europe starting with the European Payments Union (1950) as a first step towards convertibility. The first major move towards an economic and monetary union, however, was initiated by the Werner report of 1970. It called for a completion of a monetary union by 1980 through a three-stage approach leading eventually to fixed exchange rates and a common monetary policy. However, due to financial turmoil (the collapse of the Bretton-Woods system) the Werner Plan failed to succeed. Only a few elements of the Plan survived, amongst which the intra-European exchange-rate management system, also known as ‘the snake’. The snake restricted the band of the European exchange rates with the US dollar, such that the intra-European exchange rate band would not be too wide. However, the ‘snake’ was not very successful in limiting exchange rate fluctuations: several countries joined or withdrew from the system, while other exchange rates experienced devaluations or revaluations.

March 1979 was the start of the European Monetary System (EMS) with the goal to create a zone of monetary stability, consisting of all EU members. However, not all of these members joined the cornerstone of the EMS, namely the Exchange Rate Mechanism (ERM). The ERM kept each currency within a certain band defined by a grid of rates for the various pairs of currencies that could only be changed by mutual consent. At the start the number of realignments was relatively high and always *vis-à-vis* the German Mark. In the 80’s realignments occurred less frequently due to monetary policy changes and from 1987-1992 there were no revaluations at all, since the central rates of the ERM were considered to be very credible.

In the beginning 1992 it looked like the ERM would slowly converge to the EMU. However, stabilized expectations changed dramatically after the Danish rejected their participation with the EMU through a referendum. This moment is usually indicated as the trigger that initiated the ERM crises in 1992-1993. As a consequence, most currencies came under attack and the UK Pound and Italian Lira even left the ERM system. Exchange rate markets only tranquilized after the fluctuations margins were widened to 15 per cent (coming from 2.25 or 6 per cent for different rates). After the crisis was settled, the smooth transition towards the EMU did take place after all. Exchange rates fluctuated around their central rates and Austria, Italy, Finland and Greece joined the ERM system (as participation in the exchange rate system was one of the convergence criteria for participation in the EMU).[1]

The start of third stage of EMU took place at 1 January 1999 by fixing the exchange rates of the eleven participations countries that fulfilled the convergence criteria (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain). Two years later Greece also adopted the euro, while Denmark, Sweden and the U.K. chose not to join the EMU. The euro coins and paper were introduced on 1 January 2002, three years after fixing the exchange rates. As of 1999 the European Central Bank has been responsible for deducting the monetary policy in the euro area in cooperation with the central banks of the member states (called European System of Central Banks).[2]

Though the monetary integration process finally managed to create a monetary union, the European integration process is far from finished. Monetary integration is a necessary condition for the financial integration of bond and equity markets. “Financial market integration is of great importance for the smooth functioning of EMU. The main reason is that it can function as an insurance mechanism facilitating adjustment to asymmetric shocks” (De Grauwe, 2003). The elimination of exchange rate risk between EMU-countries has eliminated an important obstacle for the complete integration of financial markets. Adjaouté and Danthine (2003) report that the bond markets have integrated very rapidly around 1999. The redemption yields on the government bonds of different EMU-member states have almost disappeared and the spread between these yields is mainly caused by different default probabilities of the governments under consideration. The integration of equity markets is much more time consuming. De Grauwe (2003) states that full integration of equity markets still is hampered by legal and regulatory differences. Therefore, a country-specific risk factor may still apply to stock prices, although the exchange rate risk has disappeared. This thesis concentrates on the integration of equity markets. We test whether the structural changes in the euro area have had any consequences for investors already. However, the academic literature does not provide a uniform methodology in testing for asset market integration. In this thesis a number of different methodologies to study the issue of integration are presented.

[1] See Gros and Thygesen (1998) for more details on the ERM crisis and the convergence to the EMU.
[2] See Eijffinger and De Haan (2000) for a description of the ECB and ESCB and its tasks in terms of monetary and fiscal policy.

1.3 Asset pricing consequences

The brief discussion in the previous sections makes it clear that Europe or the euro area is an interesting region for research. After all, the introduction of the euro made the EMU the biggest financial counterpart of the U.S. Therefore the asset markets of the EMU are receiving increasingly more attention from investors, which feeds the relevance of this dissertation. In order to do research on financial markets of the euro area, it is crucial to take both global and regional developments into account. Though it is impossible exactly to contribute each part of the returns to specific causes, it is crucial to keep these developments in mind when performing research. This section will shortly elaborate on some of the changes that have to be taken into account.

Most noticeable is the elimination of the exchange rate risk between the euro participating countries as of 1 January 1999. However, all studies in this dissertation use data with a history that goes back further than this date. This means that this structural break has to be taken into account in some way. Roughly speaking, there are two different approaches to incorporate this. The first method is to take the view of one specific investor. All returns before 1999 are then translated into the home currency of this investor, such that they are comparable. In the literature it is common to use the German investors as a representative for the German investor. We employ this view in chapters 2 and 3. The other possibility is to study local returns for all securities. The exchange rate risk is then either neglected (since it does not affect the results or it would be wrong to translate the returns into another currency) or exchange rate factors are explicitly modeled in the framework. The latter method is applied in chapters 4 and 5, while chapter 6 uses the former.

Another important, but perhaps not so well known, change is the liberalization of the rules for institutional investors. Around 1990, all European pension funds were very restricted in their investments in stock markets. First of all, the percentage of funds in stocks was very restricted and, secondly, most of this money could only be invested in home-currency denoted stocks. In the last decade of the 20th century these rules were relaxed substantially. Not only are investors allowed to invest more in stocks in general, but also to invest more in foreign stocks. Furthermore, the introduction of the common currency enlarged the universe of eligible stocks for the pension funds of euro participating countries. In other words, institutional investors have increased their holdings in European stocks as a result of both the common currency and the relaxation of restrictive rules on their foreign equity position. As a result of both these issues, institutional investors have changed their investment styles in European stocks towards a more sector-oriented approach. This demand-driven development is an important factor for several chapters in this thesis and mostly visible in chapters 2 and 5.

The last topic we want to mention is the huge influence the developments in the information technology (IT) industry have had on stock markets in general. It is clear that the IT-sector has changed our lives in a relatively short period of time. The availability of computers and especially access to the internet for practically everybody in the world has had a big impact. First of all, there is less information asymmetry because information is easily accessible and quickly available. Secondly, there are more products available and there is a higher degree of competition. The arrival of the information technology precipitated the introduction of more complex instruments and products. Also, the access to these and other existing products is much easier through the internet and it makes the competition fiercer. The third impact of the technological development is the large influx of IT-companies in the last decade of the 20th century and the following 'IT-bubble' around the turn of the century. The new sector flourished and many start-ups seized the opportunities in these markets. Many of these firms went public and attracted capital from the financial markets. As a result of the favorable prospects and the extremely high growth rates, stock prices rocketed to unprecedented levels. This phenomenon is known as the IT-hype or bubble. The hype started more or less around 1994 and boomed in 1998/1999, while the bubble burst in 2000. The bubble attracted a lot of media attention through the never-ending rise of stock prices and the 'easy profits' that could be made.

These three important topics (the elimination of exchange rate risk in the euro area, the liberalization of pension fund regulations and the developments in the IT-sector) show that the investor has to be careful in making forecasts for euro area stock markets. For example, for making cost-of-capital calculations or creating optimal portfolios, it is doubtful whether long series of historical returns are still representative for the future distribution of returns. Hence, both academics and practitioners should perform careful and up-to-date research in order to develop expectations for European stock market returns and risks. This thesis presents some studies in this area.

1.4 Outline

The core of this thesis consists of five chapters divided over two different parts. Part I (chapters 2 – 4) studies the diversification opportunities in the euro area stock markets and tests different asset pricing models. Part II (chapters 5 and 6) focuses on the European banking sector, examining both the level of integration among bank equity prices and their associated risks. In this subsection we briefly discuss the set-up and main conclusions of each of these chapters.

Chapter 2 starts with a focus on the diversification opportunities among different categories of stocks. The study adds to the discussion on the well-known country and industry effects. The literature on these effects tries to disentangle the sources of risk on the basis of two clear characteristics of the underlying firms: the geographical base country and the (dominant) industry the firm operates in. The seminal paper of Heston and Rouwenhorst (1994, 1995) provides a simple methodology and shows that geographical information is more important than sector information. Many studies closely follow their methodology and find similar results. However, recent research by Cavaglia, Brightman and Aked (2000) and Adjaouté and Danthine (2001a, 2001b, 2002), amongst others, shows that the industry information is becoming more important relative to the country information. Moreover, it is expected that this turnover is stronger in the euro area, although Rouwenhorst (1999) cannot find any evidence in his pre-euro sample.

Parallel to the discussion on the declining ratio of country effects over industry effects (as sketched above), the empirical methodology of Heston and Rouwenhorst (1994, 1995), which is employed by most authors, is questioned. Brooks and Del Negro (2002) and Adjaouté and Danthine (2002) provide evidence that the underlying assumptions of the original methodology are too restrictive and advocate other or more complex techniques for these types of studies. Chapter 2 tries to fill this gap through the use of a different methodology applied to the euro area specifically. We go back to the theory of Markowitz (1952) who solves the portfolio optimization problem in a mean-variance utility framework. Using this framework we can easily show which investment category provides the best diversification opportunities. We compare the mean-variance frontier of country indices only with the frontier composed by sector indices only. For our recent sample since 1995 of euro area stocks, we find that an investor is better off diversifying over different sectors compared to diversifying over different countries alone. This conclusion is supported by spanning and intersection tests, especially after the introduction of the common currency. Furthermore, we show that this result is very robust. We find the similar results when we exclude the IT-sector index and other related indices. The IT-hype only strengthened this paradigm shift. Lastly, we show that our conclusions are also valid for different volatility regimes, where the level of the volatility is estimated through a multivariate GARCH model.

In chapter 3, we go one step deeper and study the 'domestic' three-factor model (3FM) based on the Fama and French (1992, 1993, 1995, 1996) methodology for the euro area stock markets. The original 3FM was like the Capital Asset Pricing Model developed as a global asset-pricing model. However, empirical research has shown that asset pricing from a domestic viewpoint is not exactly similar to pricing the same assets from a foreign perspective. Only in the case when no frictions exist, like transaction costs, information asymmetry and others, should asset pricing follow a global model. Empirical puzzles like deviations from the purchasing power parity and the home bias are likely consequences of these frictions in the markets. Therefore, many academics and practitioners use local versions of the CAPM and the Fama and French three-factor model. Even stronger, Griffin (2002) shows that a domestic version of the 3FM has a better performance than the global version for the Canada, Japan, U.K., and U.S., providing clear evidence that a domestic model is preferred. In this chapter we investigate which 'domestic' model an investor should pursue for euro area stock markets. Before the introduction of the common currency, a country 3FM would intuitively be most appropriate, but this intuition is less strong now the exchange rates are frozen and a euro area 3FM is more suitable. Using a sample from 1991 till 2002, we show that the country 3FM has a better performance than the euro area version, but the difference is clearly disappearing, which we attribute to the rise in the level of European integration. Next to that, we also investigate the performance of an industry-specific 3FM versus the euro area 3FM. We find that the industry 3FM outperforms the euro area version of the model in pricing industry portfolios.

Chapter 4 explores the relationship between inflation risk and asset pricing in an international context. The starting point for this chapter is formed by the International CAPM (ICAPM) as described by Adler and Dumas (1983). In this model asset prices are related to market risk and to real exchange rate risk, since investors are mainly concerned with asset returns in real terms. By definition, real exchange rate risk can be decomposed into nominal exchange rate risk and inflation risk. In the literature, most empirical evidence of the ICAPM is based on the assumption that the inflation rates are non-stochastic and showed that nominal exchange rate risk is priced for international asset returns. In chapter 4 we let the inflation differentials (with respect to the numeraire country inflation) be stochastic as well. The empirical results in this chapter show that next to market and nominal exchange rate risk, inflation rates form a significant source of risk as well, both statistically and economically. Additionally, we demonstrate that the risk premium for inflation risk is similar in magnitude to the risk premium for nominal exchange rate risk, implying that investors are more risk averse to inflation risk than to currency risk. Lastly, we test whether the ICAPM holds during our sample and we find that the data does not support the ICAPM.

Chapter 5 is the first chapter that concentrates on the European banking sector. Since an integrated banking sector is essential for the European integration process, European banking regulations have been harmonized to a high degree over the last few decades in order to create the pathway for a single banking market. Nevertheless, the European banking industry remains fragmented, as shown by the relatively high market shares of banks in their home countries (Dermine, 2003) and the fact that more 90% of the loans granted by banks in the euro area are to domestic residents (De Grauwe, 2003). Though the real integration among European banks may still be lower, the level of financial integration among those banks might show a different pattern. Therefore, chapter 5 examines the integration process of bank share prices for 41 European banks. The main finding is that the correlation between larger banks in Europe has increased substantially over our sample period (1991-2003), whereas the correlation between smaller banks has become lower. A reason for this result could be that investors perceive that the activities of bigger banks are becoming more correlated, while smaller banks seem to be becoming more specialized. Another reason may be that as a result of institutional and other larger investors turning their investment strategies towards a European sector-based approach, investors increasingly track indices of the European banking sector. These indices are typically constructed from the stock prices of the larger banks. This provides a new angle on the discussion of possible strategic choices for banks, which are discussed as well.

In chapter 6 we examine bank contagion within the European Union, building on the approach by taken by Bae, Karolyi and Stulz (2003). The approach is related to the growing conviction that the behavior of tail observations for financial market data is quite different from the behavior of other observations. Bae, Karolyi and Stulz (2003) provide evidence that the number of tail observations is inconsistent with the number of observations that would be expected from a normal distribution or even a student t distribution. We confirm this belief for European banks' risk, measured both by the first difference of weekly distances to default and abnormal returns. Using Monte Carlo simulation we show that the observed frequency of large shocks for European banks can also not be explained by these distributional assumptions. Therefore, we propose a non-parametric approach in the second part of this chapter, that we label "net-contagious influence". We show that this measure should give an accurate indication of contagious influence between two banks. Also, we identify those banks that appear to have been of systemic importance within individual countries and across countries.

Chapter 7 presents a summary and a conclusion of this thesis.

Part I

Diversification and Asset Pricing in the Euro Area Stock Markets

Chapter 2

Diversification in Euro Area Stock Markets: Country vs. Industry

2.1 Introduction

The extent to which financial markets and countries have become more integrated has been the topic of extensive debate. Capital markets in the euro area are an interesting subject of study, because of the rapid changes caused by the unification process and the introduction of a common currency. Our research question concerns the consequences of the ongoing European integration for investors in the euro area in terms of stock market diversification. In this chapter we concentrate on the differences between investments strategies based on country factors and on industry factors. [3]

Prior empirical research found that country factors dominated industry factors in explaining stock returns (e.g. Roll, 1992; Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998; Rouwenhorst, 1999). These papers concluded that investing according to a

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[3] For a more detailed discussion on European integration and changes in the European regulation system, see e.g. Hardouvelis, Malliaropulos and Priestley (1999), De Menil (1999) or Adjaouté and Danthine(2002)

pure country strategy outperformed a strategy based on information from industries only. In terms of portfolios, Heston and Rouwenhorst (1995) show that more diversification gains can be obtained when an investor diversifies over countries (compared to diversification over industries).

More recent research, however, finds mixed results. According to Carrieri, Errunza and Sarkissian (2004), Gerard, Hillion and De Roon (2002) and Adjaouté and Danthine (2001a, 2001b) the dominance of country effects has diminished, but industry factors are still less important than country factors. On the other hand, Cavaglia, Brightman and Aked (2000) and Isakov and Sonney (2002) show that industry factors (almost) match the country factors and expect that industry factors will become even more important. This conclusion is confirmed by the extension of the Rouwenhorst (1999) methodology. In his original paper he concludes that country effects still dominated industry effects in the 90's (based on a sample until August 1998), while a figure on his website shows that the industry effects will take over during 2000.[4]

Brooks and Del Negro (2002, 2004, 2005) discuss this topic on a global scale from different points of view. Brooks and Del Negro (2004) focus on the fact that the rise in the industry effects coincided with the information technology/internet "bubble" (hereafter IT-hype). When one corrects for this phenomenon it follows that the upward trend of the industry effects is less pronounced. In their second paper Brooks and Del Negro (2005) use an adjusted version of the Heston and Rouwenhorst (1994, 1995) methodology to investigate the relative importance of industry, region and within-region effects. They conclude that regional effects can explain the country effects for 60 up to 90%.

The third paper of Brooks and Del Negro (2002) discusses the drawbacks of the Heston and Rouwenhorst (1994, 1995) methodology, which is followed by most other papers. This methodology follows a dummy approach where all companies are a member of exactly one country and one industry. Clearly, this is a very strong assumption, especially for big multinational firms. Brooks and Del Negro (2002) show that a less restrictive model performs better (according to the Akaike and the Schwarz Information Criterium). A similar argument is put forward by Adjaouté and Danthine (2002), who also criticize the standard Heston and Rouwenhorst (1994, 1995) methodology.

Summarizing, it seems that until approximately the middle of the 90's country factors were dominant factors in explaining stock returns. Around the turn of the century more and more signals show that industry effects are increasing. Some studies (for example: Cavaglia, Brightman and Aked, 2000; Brooks and Del Negro, 2004) report that on a global scale industry effects are taking over, however, this result is no longer valid as

[4] K.Geert Rouwenhorst, K.Geert Rouwenhorst's homepage, Yale School of Management, http://mayet.som.yale.edu/geert (accessed March 02, 2004).

soon as one corrects for the IT-hype. For the European area, the evidence is a little bit more in favor of the industry factors, even after correcting for the extreme rise in the information technology assets. However, all of these results are based on the restricted Heston and Rouwenhorst (1994, 1995) methodology, while Brooks and Del Negro (2002) show that an unrestricted version of this model is statistically preferred.

In this study we want to test whether sector-based diversification strategies obtain higher diversification benefits than country-based strategies, applied in the euro area markets. A priori, a confirmation of this hypothesis would not be a surprise, since it is expected/forecasted by economists. Already during the run-up to the introduction of the common currency, economists expected sector-based diversification strategies to become more important and slowly institutional investors redesigned their departments to take this into account. However, Rouwenhorst (1999) could not find any evidence of this expected shift with a sample until mid 1998. We revisit this issue with recent data and compare it with the results of Rouwenhorst (1999), amongst others.

This chapter is not aimed at contributing to the (methodological) discussion on the relative significance of country and industry factors. Rather, we concentrate on the consequences of the changing structure of asset returns in Europe for asset management. This is also our main contribution to the literature: we go on step further and directly investigate the consequences of the changes in the markets for the portfolios of the investors.

The comparison of portfolios is done by standard mean-variance analysis. Using industry and country indices from the period 1995 till 2002 we construct mean-variance frontiers and directly compare the efficient portfolios. We show that industry-based diversification yields more efficient portfolios than country-based diversification in the euro area nowadays. The result is in compliance with the expectations based on economic theory, but in contrast with previous studies like Rouwenhorst (1999). We also show that this is result is robust to changes in volatility and robust with respect to IT-hype around the turn of the millennium. The implication for asset managers is that they should generally no longer base their euro area portfolio on a country-diversification strategy.

The rest of this chapter is organized as follows. In the section 2.2 we describe the methodology used in this chapter. Section 2.3 discusses the data. The results are presented in section 2.4 and section 2.5 concludes.

2.2 Methodology and model specification

The main research question that we want to answer is whether diversifying over countries or diversifying over industries is the better strategy for the euro area. Then, before discussing the details of the methodology used, let us briefly review some underlying economic intuition.

When we consider the pricing of European stocks, several different factors are important. For a specific European stock we can distinguish three different types of factors: country specific factors, industry specific factors and other (European) factors (see also Carrieri, Errunza and Sarkissian, 2004). European factors, like the interest rate (which is equal for all European Monetary Union members after the introduction of the common currency) and the exchange rate of the euro with other currencies like the U.S. dollar and the Japanese yen are the common factors that drive all stock returns. We expect that the shocks from these common factors will have the same impact during the integration process or may even become more important.

The effect of country specific factors is expected to decline over time during the integration process of the European countries. For example, the above mentioned interest rate is no longer a country specific factor as of the introduction of the common currency. Also, as of 1999 the exchange rates between EMU countries were fixed, which eliminates the exchange rate risk. On the other hand, some country factors will still remain. Investment barriers (like transaction costs) for investing in stocks of other European countries are lowered over time, but the costs of international investments are still higher than the costs of investing in domestic stocks. The difference between these costs may be an important reason for the home-bias effect[5] and the explanation for the relevance of the country factors. Other examples of country factors are differences in tax regimes, inflation rates, economic activity, legislation and natural events (like flooding) that have an impact on the economy.

The last set of factors is the industry factors. This type of factors is very important for pricing of individual stocks. R&D investments, mergers, acquisitions or bankruptcies within an industry drive market share, market value and returns of firms in that industry. We do not expect that the impact of industry shocks has changed very much over time in Europe. However, the relative importance with respect to country specific factors is expected to increase.

Clearly, the numbers of factors that might have an influence on stock returns is very large, too large to specify them all. Moreover, we do not know the importance of each different variable and sometimes it is hard to find correct data that represent the (risk) factors we described. Therefore, like most papers in this field, we will not try to specify all possible factors.[6] Several of these studies show that the proceeding economic integration among euro area countries has important consequences for the factors driving asset returns in financial markets. In this study we want to concentrate on the implications of the

[5] See e.g. Cooper and Kaplanis (1994) and Lewis (1999)

[6] See Fratzscher (2002) for a specification that includes several important factors. He finds that the central driving force in the financial integration process in Europe is reduced exchange rate volatility and the monetary policy convergence of interest rates and inflation rates.

changing structure of security returns for asset management. This will be done using the conventional theory of mean-variance analysis. The approach is relatively straightforward and intuitively appealing. In order to keep the calculations tractable we apply this methodology to stock indices rather than a to broad set of individual stocks.

Section 2.2.1 discusses the Markowitz (1952) mean-variance methodology. In the following section we describe the spanning and intersection tests that we use to compare the different efficient frontiers and the last section covers a multivariate GARCH-methodology. This approach is used to see whether are conclusions are robust for different volatility regimes.

2.2.1 Mean-variance frontiers

The unconditional portfolio optimization problem will be solved according to the methodology proposed by Markowitz (1952) who solves the problem from the point of view of an investor with a mean-variance perspective. Given the means – which are estimated by the historical averages – and the covariance matrix of both the country and the industry indices we plot the mean-variance frontiers. The standard Markowitz (1952) mean-variance efficient frontiers follow from this optimization problem.

$$\begin{aligned} \min_{w} \quad & \frac{1}{2} w' \Sigma w \\ s.t. \quad & w' \mu = R, \\ & w' \iota = 1 \end{aligned} \qquad \textbf{(2.1)}$$

where w represents the weight invested in each index, μ is the average return, Σ represents the corresponding covariance matrix of the return indices and ι is a vector with all elements equal to one. The investor minimizes the amount of risk of his portfolio as measured by the portfolio variance given a certain demanded return R and subject to the budget restriction that all weights should sum up to one. In this chapter we will do the analysis for country and industry indices separately to obtain two efficient frontiers. Additionally, we perform the same analysis for all investment opportunities (country and industry indices together) to see the influence of the added indices. Naturally, this frontier will give the best investment opportunities, since the other two investment strategies are nested.

2.2.2 Spanning and intersection tests

In the unconditional analysis we use spanning and intersection tests to find out whether an investor can gain by considering more investment opportunities. The tests are described in for example De Roon and Nijman (2001) and are based on regression analysis. Intuitively, they are relatively straightforward. An investor chooses an efficient portfolio given one set of investment opportunities (in our case indices). The introduction of the second set of indices increases the number of investment opportunities. The test gives an answer to the question whether the investor can significantly improve his portfolio by investing in the other indices as well. In other words, from a mean-variance frontier point-of-view, adding assets to the current portfolio will lead by definition to a shift of the frontier. A rejection of the spanning test means that this shift is statistically significant. The intersection test tests whether an investor can improve his efficient portfolio given a certain risk-preference or risk-free rate. The spanning test compares the whole set of efficient portfolios and tests whether the addition of the other set of indices gives significantly better portfolios. The rest of this section explains the tests in detail.

Regression analysis can be used to test whether the inclusion of extra investment opportunities really enlarges the efficient set of portfolios. For example, when we test whether the inclusion of industry indices is important, we regress the returns of the industry indices on the country indices returns (compare equation 20 of De Roon and Nijman, 2001):

$$R_{ind,t} = \alpha + \beta \cdot R_{cou,t} + \varepsilon_t \tag{2.2}$$

where $R_{ind,t}$ is $Kx1$ vector of industry index returns for time t, $R_{cou,t}$ is an $Lx1$ vector of country index returns for time t, ε_t is a $Kx1$ vector of normally distributed error terms, α is a $Kx1$ vector of constants and β is a KxL vector of slope coefficients. The test for intersection and spanning can now be defined as a Wald-test on the estimated parameters. The restrictions imposed by the null hypothesis of intersection are:

$$\alpha - \eta \cdot \left(\iota_{ind} - \beta \cdot \iota_{cou}\right) = 0 \tag{2.3}$$

where ι_{ind} and ι_{cou} are $Kx1$ and $Lx1$ unit vectors respectively with all elements equal to one. From the dimensions it is clear that the intersection test is a Wald-test of K restrictions at the same time, where K is equal to the number of new investment opportunities introduced. The test-statistic has a χ^2-distribution with K degrees of freedom. The intersection test tests, given a specific value for η, whether mean-variance investors can improve their mean-variance efficient set by including the other set of indices. η can be seen as the interest rate. We used a rate of 3% per annum, thus η=1.0025 (the monthly rate in gross return).[7]

The null hypothesis of the spanning test can be stated by the following restrictions:

$$\alpha = 0 \quad and \quad \beta \cdot \iota_{cou} - \iota_{ind} = 0 \tag{2.4}$$

[7] The results are fairly robust. There are some minor changes in the p-values of the tests, but these do not change the conclusions.

This test consists of $2*K$ restrictions and the Wald-statistic is χ^2-distributed with $2*K$ degrees of freedom. It is easy to see that this test is more restrictive than the intersection test: if the restrictions in equation (2.4) hold, by definition the restrictions in equation (2.3) hold. For a more detailed discussion on the characteristics of the specific tests, see De Roon and Nijman (2001).

To summarize, in the case that the intersection test is rejected, it means that the mean-variance frontiers of the country indices and of both types of indices do not intersect for this specific interest rate and that this investor can find a significantly better portfolio by spreading his investments over both investment categories. When the hypothesis of spanning is rejected, we can conclude that the country indices do not span the universe of both types of indices or, in other words, that every investor is better off considering both investment categories.

2.2.3 Conditional Covariance Matrix

It is a stylized fact that the volatility of stock returns is not constant of time (heteroskedasticity). Especially over shorter horizons (e.g. when returns are measured on a daily or weekly basis) stock returns tend to display volatility clustering. This characteristic is important for managers that try to time the market. In addition, time-varying return volatility and cross-correlation also matters from a risk management perspective. One of the first models that incorporated this feature is the ARCH-model developed by Engle (1982), later generalized by Bollerslev (1986) to the GARCH-model. This section covers a multivariate version of the GARCH-model in order to capture the dynamics of the volatilities and correlations.

We will use this model to check the validity of our conclusions with respect to different volatility regimes. Combining the historical means (μ) and a conditional covariance matrix (H_t) in the investor's minimization problem (as described in section 3.2.1) results in the conditional mean-variance frontier. We are mainly interested in three different cases:

1. A period when the overall volatility is very low on average
2. A period when the overall volatility is very high on average
3. The last time period considered.

The first two cases are used as robustness tests on the analysis. Hence, we consider two different volatility regimes. The last case is interesting, because it takes all information into account. As mentioned above, euro area stock markets have experienced substantial structural changes since the introduction of the euro, and joint stock return distributions estimated over samples which extend far back into the past might not any more be sufficiently representative. Therefore, the last conditional covariance matrix might be insightful.

It is very important to have an accurate estimate of the conditional covariance matrix. However, this is not a trivial issue, especially when the number of variables becomes large (because the number of parameters increases exponentially). We will use a special methodology for estimating the covariance matrix: principle components GARCH or O-GARCH, as proposed by Alexander (1998, 2001, 2003). The remainder of this section explains the model in more detail.

We use a multivariate GARCH-model or, more accurately, Orthogonal GARCH also known as Principal Component GARCH (which is nested in the more general BEKK model, see Van der Weide, 2002) in order to estimate a time-varying covariance matrix. Most research concerning the time behavior of the correlation coefficient uses a bivariate model (e.g. Longin and Solnik, 1995), which gives a detailed description of the co-movements of the two time series considered. However, we are more interested in the time patterns for all indices in one system. Therefore, employing a multivariate model instead of using a number of different bivariate models is an important improvement.

The multivariate model for asset returns can be written as:

$$R_t = E(R_t) + \varepsilon_t \qquad\qquad \varepsilon_t \sim N(0, H_t) \tag{2.5}$$

where R_t represents a vector returns on period t (this can be the returns all country indices returns, the returns of all industry indices or the returns of both types of indices) and the vector ε_t represents the error terms, which are assumed to be jointly conditionally normally distributed. H_t is the time-varying covariance matrix. In this chapter we will use the historical average of the returns for the expectation of the asset return ($E(R_t)$). In future research this can be extended by conditioning on information variables, like the dividend yield, the term structure spread, the short-term interest rate and the default spread.

The matrix H_t is the conditional covariance matrix of the vector error term ε_t. An important part of this model is the specification of H_t, because the number of parameters can be very large as soon as the number of return series is higher than two or three. In our case (using 10 industry and 11 country indices) it is necessary to find alternative ways to estimate the conditional covariance matrix. Different studies proposed methods to study the changing correlations between assets.[8] We use the Orthogonal-GARCH method (hereafter O-GARCH) as proposed by Alexander (1998, 2001, 2003). This method transforms the series into independent series (the unobserved economic variables or the principal components), which reduces the number of parameters dramatically.[9]

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[8] See e.g. Longin and Solnik (1995) and Engle (2002). Especially the last method is very interesting when one wants to study the time-behaviour of volatilities and correlations.

[9] In some recent work Van der Weide(2002) proposes a generalized version of the Orthogonal GARCH, also called GO-GARCH. This version should have less identification problems and give better estimation results, especially when the data are independent. In our case the data are far from independent and some preliminary tests showed that the differences of GO-GARCH compared to O-GARCH are not large. Since we use monthly

We define the standardized return series as follows:

$$x_{it} = \frac{R_{it} - \mu_i}{\sigma_i} \tag{2.6}$$

where μ_i and σ_i are the mean and standard deviation for the return series R_i. Let X be the matrix representation of x_{it}. Furthermore, let V be the matrix of eigenvectors of $X'X$ and Λ the corresponding diagonal matrix containing the eigenvalues. Then, the principal components (or the unobserved economic factors) are given by:

$$P = XV \tag{2.7}$$

By definition the created risk factors are uncorrelated. We can easily show that the covariance matrix of P is indeed diagonal:

$$Var(P) = P'P = V'X'XV = V'V\Lambda = \Lambda \tag{2.8}$$

The variance of the standardized and original return series is then equal to:

$$\begin{aligned} Var(X) &= Var(PV') = V\Lambda V' \\ Var(R) &= Var(R - \mathrm{M}) = Var(D \cdot X) = DV\Lambda V'D' \end{aligned} \tag{2.9}$$

where M is constant matrix containing the average for each return series and D equals the diagonal matrix with σ_i its principal diagonal.

The O-GARCH method is based on this orthogonal transformation. Instead of estimating very large covariance matrix with an exploding number of parameters with a growing number of return series, we can approximate the conditional covariance matrix by estimating univariate GARCH on each of the orthogonal series pit.[10] This will result in a time-varying diagonal covariance matrix for X: Λ_t. Under the assumption that the transformation is also valid in the conditional case, the conditional covariance matrix of the original series H_t is then equal to:[11]

$$H_t = D'V\Lambda_t V'D \tag{2.10}$$

This conditional covariance matrix will be used for the creation of conditional mean-variance frontiers.

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data in this paper and the GO-GARCH model has more parameters (caused by the estimation of the so-called rotation matrix) we stick to the O-GARCH model.

[10] Since we use monthly data, the number of observations is relatively small. Hence, we do not estimate GARCH(1,1) for all series p_{it}, because not all components contain heteroskedasticity. This concerns the principal components belonging to the lowest eigenvalues. These are exactly the components that have low influence. For a longer discussion on this topic, see Alexander (2003).

[11] See Alexander (1998, 2001, 2003) for a discussion on this restriction.

2.3 Data

In empirical finance having the right dataset is very important, especially for this project. On the one hand we would like to have a very long sample of country and industry indices returns. On the other hand, we want to be able to compare the results of the different sets of indices with each other. Preferably, to be comparable, the stock indices should be constructed out of the same pool of stocks. Since we concentrate on the stocks in the euro area, it is very hard to find a dataset that combines these two characteristics (unless one creates the indices himself). We choose to use the MSCI indices that only start in 1995, because the second argument is a little more important. On top of that, one can argue that euro area markets have changed so much over time, that longer time series might not be representative for the current and future distribution of returns.

We use both industry and country indices from MSCI for all EMU-participating countries except Luxembourg.[12] The industry indices are the MSCI sector indices for the European Monetary Union area, which are based on exactly these eleven countries. The sample consists of monthly returns from January 1995 until October 2002. Since the euro was introduced on January 1st 1999, the first part of our sample still contains exchange rate risk. Therefore, we take the view of a German investor and translate all returns into German Marks. Using the US dollar/German mark exchange rate from Datastream we transformed all dollar denoted MSCI indices into German marks. The MSCI indices are price indices, since gross indices were not available for the industry indices. Table 2.1 presents the statistics for the country and the industry indices.

2.4 Results

This section presents the results of the methodology described in section 2.2. In section 2.4.1 the efficient frontiers are based on country indices, industry indices and both types of indices are discussed. By definition, the most efficient frontiers can be found by considering both types of indices simultaneously. Comparing pure country and pure industry indices shows that diversifying over industries gives more diversification opportunities. Sections 2.4.2 and 2.4.3 present robustness tests for these conclusions. We show that the results are robust with respect to the exclusion of the IT-bubble related indices and with respect to different volatility regimes respectively.

[12] In the creation of the MSCI industry indices, MSCI also neglects the stocks from Luxembourg. Therefore, we ignored these stocks as well in order to keep the datasets comparable.

Table 2.1
Summary statistics

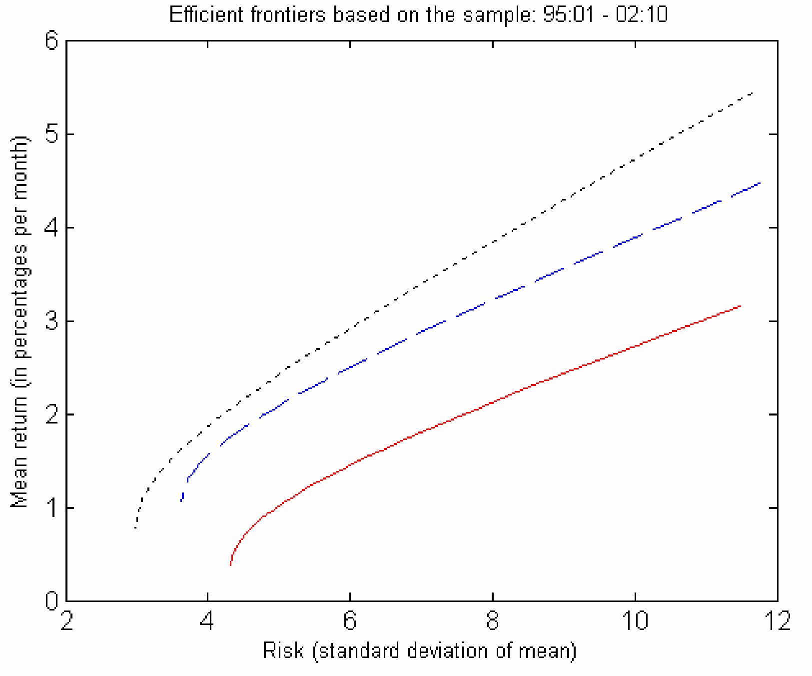
Panel A (above) shows the average monthly return and standard deviation for all the MSCI indices of the countries that form the Euro-zone (Luxembourg excluded). The statistics are presented for both the whole sample and two different sub samples. Panel B (below) presents the statistics for the MSCI industry indices.

Panel A	Total sample 95:01 – 02:10		Sub sample I 95:01 – 98:12		Sub sample II 99:01 – 02:10	
Country (MSCI index)	Return	St.dev	Return	St.dev	Return	St.dev
Germany	0.554	7.041	1.806	5.722	-0.746	8.053
Belgium	0.511	5.141	2.104	4.372	-1.152	5.397
Spain	1.174	7.061	2.821	7.232	-0.544	6.521
Finland	2.183	11.731	3.175	9.011	1.147	14.051
France	0.867	6.097	1.844	5.732	-0.152	6.358
Greece	0.744	9.372	2.611	9.837	-1.203	8.536
Ireland	0.633	5.776	2.036	4.876	-0.831	6.311
Italy	0.814	7.555	2.195	8.617	-0.627	6.021
Netherlands	0.754	5.961	2.023	5.279	-0.570	6.390
Austria	0.044	5.445	0.264	6.043	-0.186	4.799
Portugal	0.513	6.468	2.143	6.629	-1.189	5.898

Panel B	Total sample 95:01 – 02:10		Sub sample I 95:01 – 98:12		Sub sample II 99:01 – 02:10	
Industry (MSCI EMU index)	Return	St.dev	Return	St.dev	Return	St.dev
Energy	1.099	5.924	1.504	5.825	0.677	6.061
Materials	0.526	6.176	1.054	5.653	-0.025	6.697
Industrials	0.678	7.044	1.115	6.114	0.222	7.943
Consumer Discretionary	0.407	7.052	1.735	5.714	-0.978	8.051
Consumer Staples	1.049	4.678	2.399	4.894	-0.359	4.030
Health Care	1.089	5.201	2.002	5.072	0.135	5.216
Financials	0.732	7.302	2.236	6.960	-0.838	7.394
Information Technology	1.931	11.729	3.521	8.686	0.272	14.143
Telecom. Services	1.200	9.564	2.839	6.306	-0.510	11.901
Utilities	0.659	4.781	2.132	4.469	-0.878	4.653

Figure 2.1
Efficient frontiers based on the whole sample

This figure plots the mean-variance frontiers for three investment categories over the whole sample. The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.



2.4.1 Unconditional mean-variance frontiers

This section describes the results based on the full sample and two sub periods. Figure 2.1 depicts the unconditional mean-variance frontier of the total sample for three types of investments: country indices only, industry indices only and both types of indices. By definition, the best portfolio can be constructed when both investment categories are considered at the same time. Comparing countries and industries with each other we can clearly see that (over the whole sample) investing in industry indices gave much more diversification opportunities than a pure country investment strategy. From a more statistical point of view, we can say that both spanning tests are rejected (see Table 2.2 and section 2.2.2 on the explanation of the tests). This means that neither the country indices nor the industry indices span the mean-variance frontier for both types of investment

Table 2.2
Results of spanning and intersection tests

This table presents the results of the spanning and intersection tests, which are taken from De Roon and Nijman (2001). Regression analysis can be used to test whether the inclusion of some extra investment opportunities really enlarges the efficient set of portfolios. For example, when we test whether the inclusion of industry indices is important, we need to regress the returns of the industry indices on the country indices returns (compare equation 20 of De Roon and Nijman (2001)):

$$R_{ind,t+1} = \alpha + \beta \cdot R_{cou,t+1} + \varepsilon_{t+1}$$

The test for intersection and spanning can now be defined as a Wald-test on the estimated parameters. The restrictions imposed by the hypothesis of intersection are:

$$\alpha - \eta \cdot \left(\iota_{ind} - \beta \cdot \iota_{cou}\right) = 0$$

The intersection test tests whether there is one specific value of η such that mean-variance investors cannot improve their mean-variance efficient set by including the other set of indices. η can be seen as the interest rate, we used a rate of 3% per annum, thus η=1.0025 (the monthly rate in gross return) The hypothesis of the spanning test can be stated by the following restrictions:

$$\alpha = 0 \quad \textit{and} \quad \beta \cdot \iota_{cou} - \iota_{ind} = 0$$

The table is divided into two parts. Panel A presents the p-values of the different tests done when the inclusion of industry indices is considered. In case the intersection test is rejected, it means that the mean-variance frontiers of the country indices and of both types of indices do not intersect for this specific interest rate. When the hypothesis of spanning is rejected, we can conclude that the country indices do not span the universe of both types of indices. For panel B it is the other way around

Panel A: P-values of the tests whether country indices span industry indices, as measured by Wald-tests on the parameter estimates of this regression: $R_{ind,t+1} = \alpha + \beta \cdot R_{cou,t+1} + \varepsilon_{t+1}$

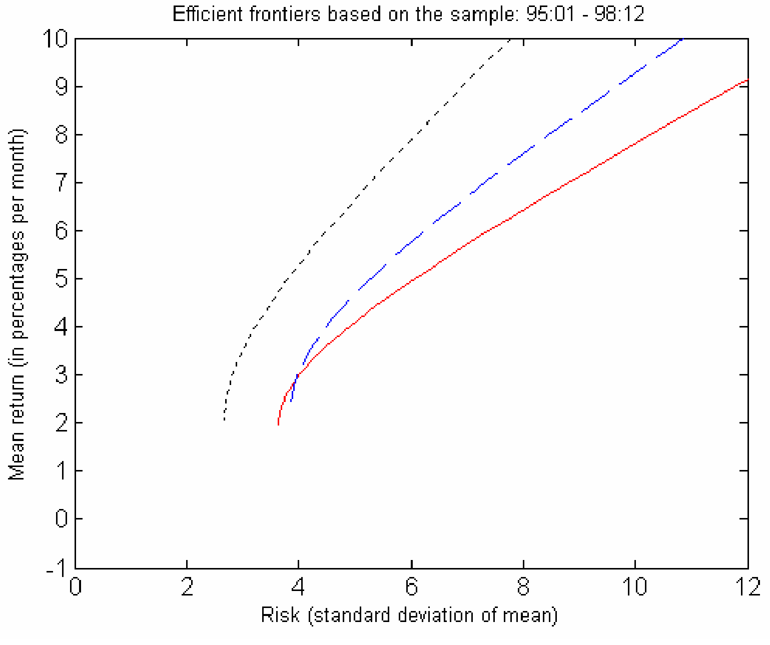
	95:01 – 02:10	95:01 – 98:12	99:01 – 02:10
Intersection test	0.754	0.177	0.956
Spanning test	0.000	0.000	0.020

Panel B: P-values of the tests whether industry indices span country indices, as measured by Wald-tests on the parameter estimates of this regression: $R_{coud,t+1} = \alpha + \beta \cdot R_{ind,t+1} + \varepsilon_{t+1}$.

	95:01 – 02:10	95:01 – 98:12	99:01 – 02:10
Intersection test	0.997	0.442	0.965
Spanning test	0.012	0.026	0.832

Figure 2.2
Efficient frontiers based on the first sub sample 95:01 – 98:12

This figure plots the mean-variance frontiers for three investment categories over the first sub sample (95:01 – 98:12). The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier line for the industry indices. The dotted line considers both types of indices.

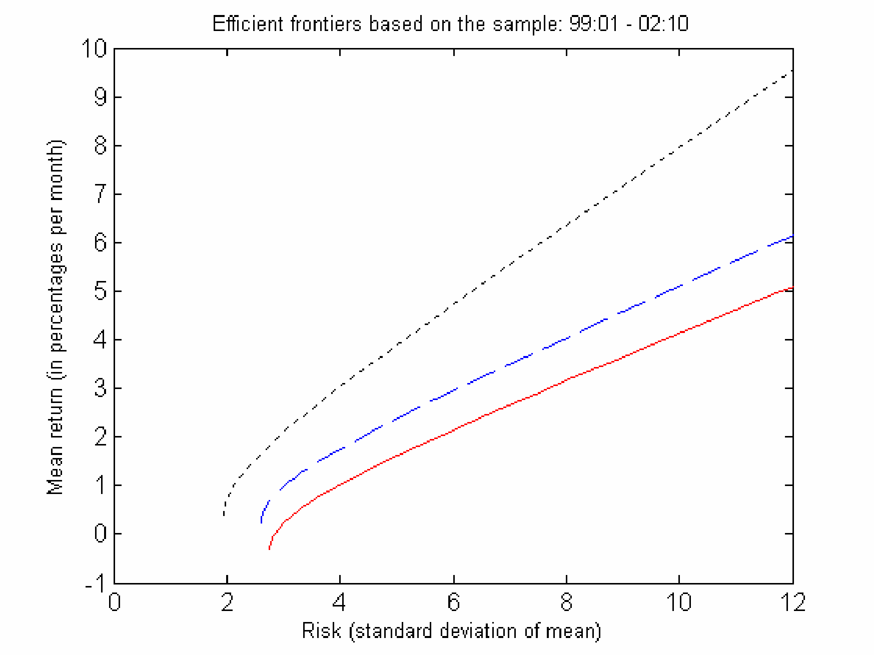


categories. In other words, a mean-variance investor can always gain by adding the other type of indices to his portfolio.

The introduction of the euro in January 1999 is a natural moment to split our sample in two halves. Figures 2.2 and 2.3 present the mean-variance frontiers of both sub samples. During the pre-euro period (Figure 2.2) a pure country-allocation scheme resulted in a similar performance as a pure industry-allocation scheme. A diversification scheme that uses both types of indices gives the best performance, which is also supported by the

Figure 2.3
Efficient frontiers based on the second sub sample 99:01 – 02:10

This figure plots the mean-variance frontiers for three investment categories over the second sub sample (99:01 – 02:10). The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.

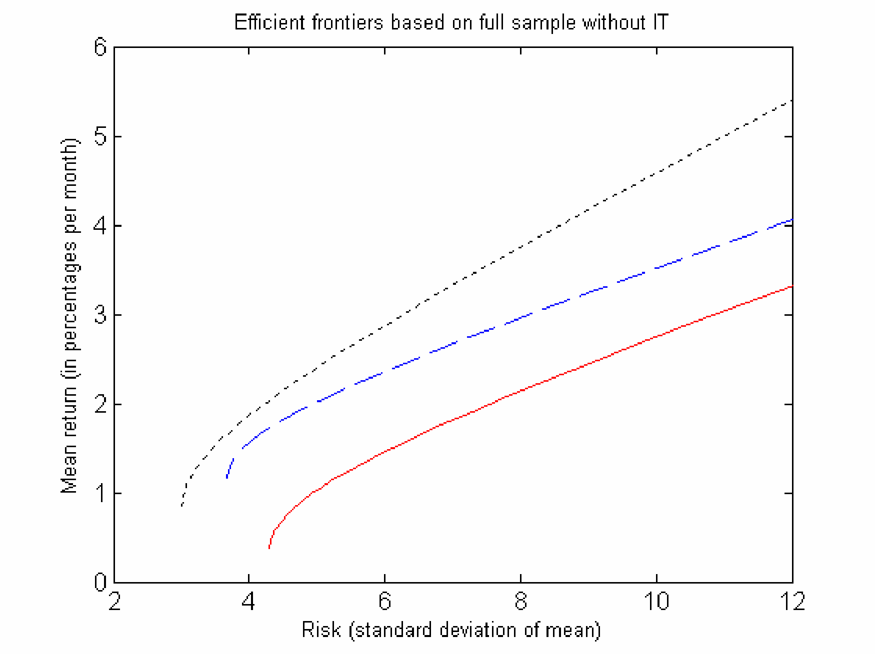


spanning and intersection tests (see Table 2.2).[13] In the second sub sample (Figure 2.3) it is clear that a more efficient portfolio can be created using industry indices compared to using country indices only. In this sample there is no exchange rate risk anymore, which could be the reason that investors are better off investing in industries. The hypothesis of intersection is not rejected (which is the case for all samples), but the hypothesis that

[13] The mean-variance frontiers for the subsamples show a clear outperformance for the diversification over both types of indices. This can partly be explained by the fact that the number of observations (four years instead of almost eight) influences the estimation of the frontiers. Therefore, we should also take the more statistical intersection- and spanning tests into account. The results of these tests can be found in table 2. The tests are described in section 2.2.

Figure 2.4
Efficient frontiers based on the full sample without the IT-sector

This figure plots the unconditional mean-variance frontier with the exclusion of the IT-sector. The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.



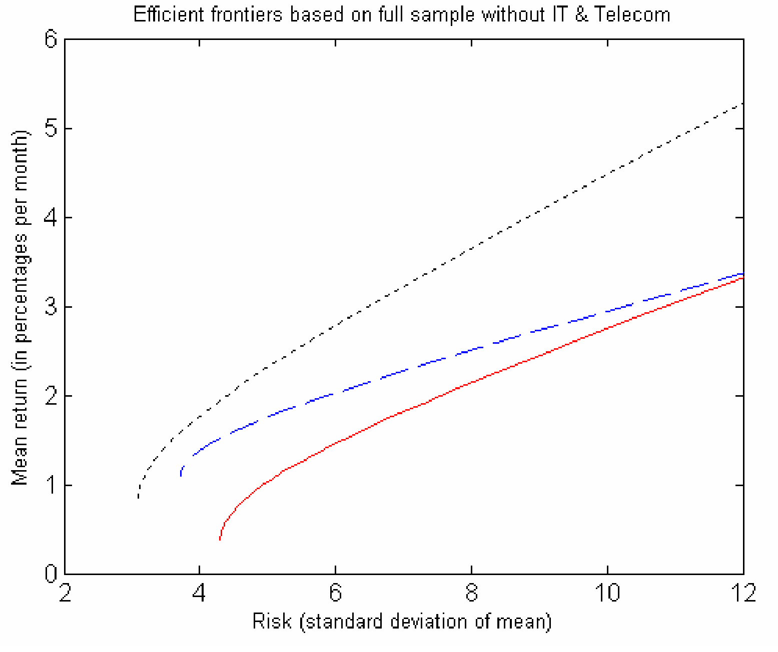
industry indices span the investment frontier of both types of indices can also not be rejected. In other words, this statistic says that the addition of country indices is not very valuable given a mean-variance efficient industry index allocated portfolio. The result is a clear indication that investing in industry indices is more important than investing in country indices nowadays.

This is in contrast with the previous literature. During the 90's the so-called country effects were more important than the industry effects (Heston and Rouwenhorst, 1994, 1995; Griffin and Karolyi, 1998; Rouwenhorst, 1999). Because of the integration process in the European area it was expected that country effects would diminish over time and that industry effects would take over, but research did not find evidence for that yet. More recent research gives ambiguous results. On a global scale, industry effects are

Figure 2.5

Efficient frontiers based on the full sample without the IT and Telecom-sector

This figure plots the unconditional mean-variance frontier with the exclusion of the IT and Telecom sectors. The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.



becoming more important, but it is not clear whether industry factors are currently more important than country factors. Our result clearly suggests that the country-diversification strategy for the euro area is outdated and that an investor (who considers indices only) should at least base his portfolio on industry factors.

2.4.2 Robustness with respect to the IT-hype

Isakov and Sonney (2002) and Brooks and Del Negro (2004) correctly state that the rise in the industry effects coincided with the rise of the technology stocks. A robustness check on the sensitivity of our conclusions with respect to this phenomenon is therefore appropriate. We follow Isakov and Sonney (2002) and Brooks and Del Negro (2004) by studying the conclusions in case the regarding indices are left out of the sample.

Figure 2.6
Efficient frontiers based on the full sample without the IT-sector, the Telecom-sector and Finland

This figure plots the unconditional mean-variance frontier with the exclusion of the IT-, the Telecom-sector and Finland. The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.

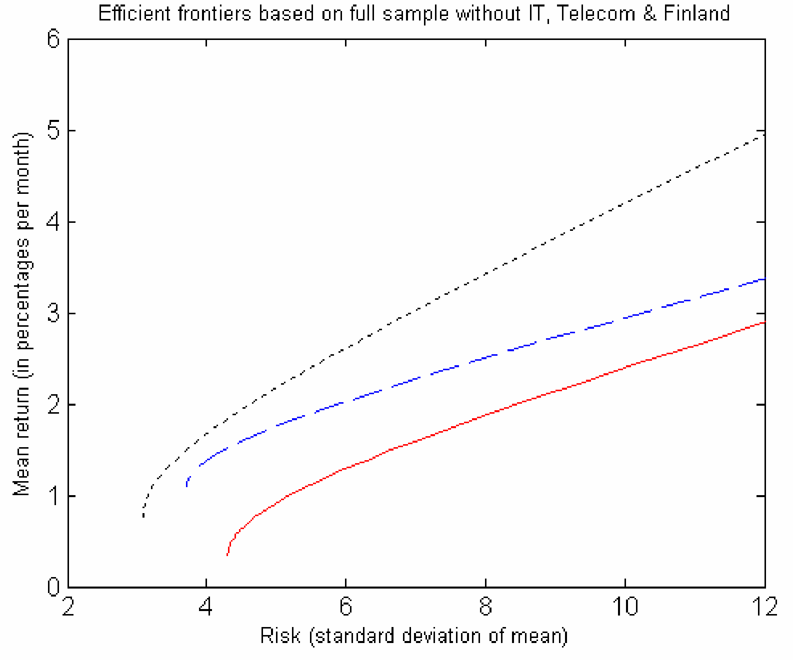


Figure 2.4, 2.5 and 2.6 show the mean-variance frontiers based on a restricted sample: excluding the IT-industry, excluding IT and the Telecom industries and excluding IT, Telecom and Finland, respectively.[14] We should add that correcting for this

[14] The exclusion of the Information Technologies and Telecommunication Serviced industries is clear (also following the literature). We also tested the exclusion of Finland, since Nokia heavily influences the stock market of Finland. In 2000 (at the top of IT bubble and the middle of our sample) Nokia represent 64% of the total Finnish market value! Furthermore, we should add that also most other country indices contain some IT-stocks and are thus influenced by this market. However, we cannot correct for that, since we are working with indices.

Table 2.3
Results of minimum-variance portfolio and the Sharpe ratio

This table presents the statistics concerning the conditional mean-variance frontiers (Figures 2.8 till 2.10) all based on the unconditional covariance matrix. The third column presents the mean and standard deviation of the Mean Variance Portfolio (MVP) and the Sharpe ratio for all investment categories when all indices are included. Columns 2 to 4 give the same characteristics when IT is not included, IT and Telecom are not included or IT, Telecom and Finland are not included, respectively. For calculating the Sharpe ratio an annualized interest rate of 3% was used.

Investment Category		All included	IT excluded	IT and Telecom excluded	IT, Telecom and Finland excluded
Countries	MVP: mean	0.353	0.353	0.353	0.332
	MVP: st. dev	4.30	4.30	4.30	4.30
	Sharpe ratio	0.266	0.266	0.266	0.229
Industries	MVP: mean	1.039	1.158	1.082	1.082
	MVP: st. dev	3.61	3.68	3.71	3.71
	Sharpe ratio	0.377	0.354	0.301	0.301
Both categories	MVP: mean	0.762	0.827	0.781	0.753
	MVP: st. dev	2.97	3.01	3.08	3.09
	Sharpe ratio	0.451	0.439	0.425	0.397

phenomenon is very hard. The hype around the end of the century not only directly influenced the rise (and fall) of the IT-related stocks, but it can be argued that it also changed the investor's view about stocks and investments in general. Therefore, excluding some indices from the analysis might not be sufficient to fully check for the effects of this phenomenon.[15]

Before discussing the changes in the results we should repeat that the historical means used are based on a relatively short sample. We should therefore interpret the results

Given the good performance of these stocks the mean-variance frontier should be even lower when we could correct for that. This fact also strengthens the results we report.

[15] We thank the referee of the ECB working paper series for this point.

Table 2.4
Results of minimum-variance portfolio and the Sharpe ratio

This table presents the GARCH-parameters for all principal components that contain conditional heteroskedasticity. We used the standard ARCH-LM test with a confidence level of 10% to test for conditional heteroskedasticity. In case the null hypothesis of no heteroskedasticity is rejected, we estimate a GARCH(1,1) model on the time series of the principal component:

$$PC_{it} = c_i + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, h_{it})$$

$$h_{it} = \omega + \alpha \cdot \varepsilon_{it-1}^2 + \beta \cdot h_{it-1}$$

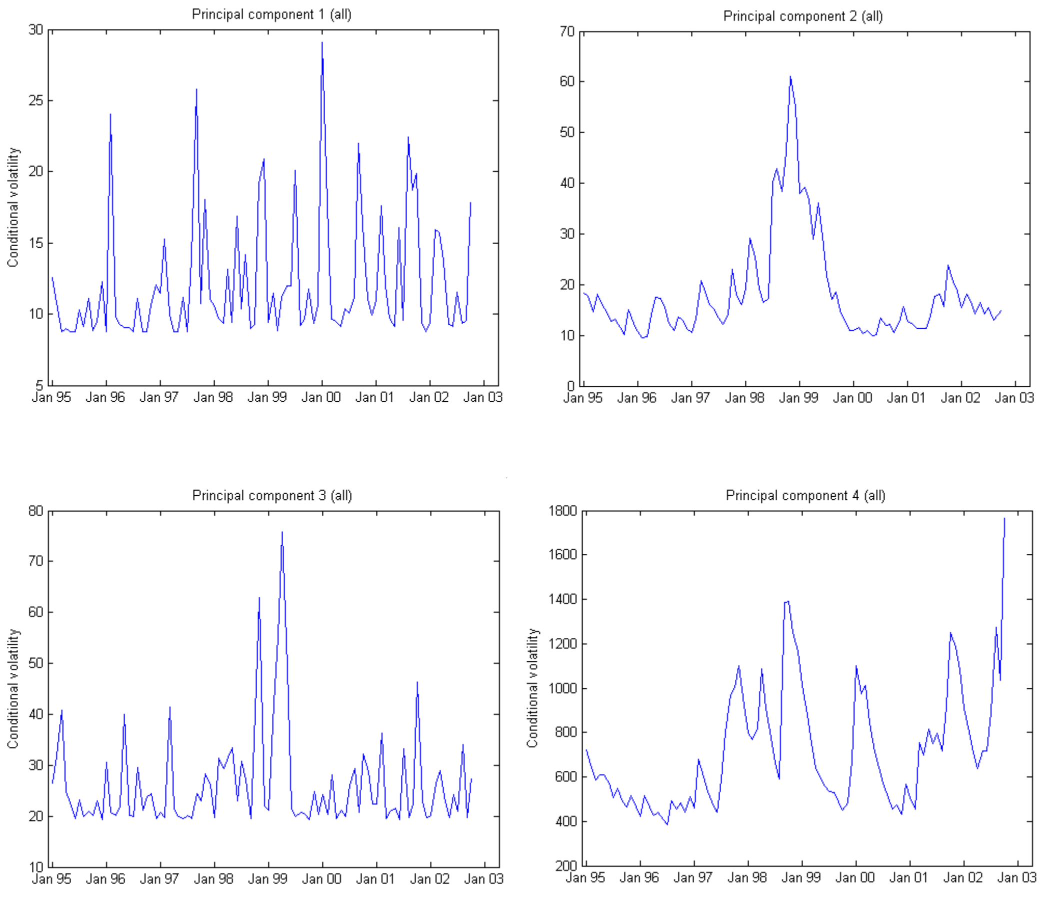
Note that the actual level of ω is not relevant, because of the transformation from the original series to the principal component series.
** means that the regarding parameter is statistically significant from zero based on a 95% confidence interval

	GARCH-parameter	ω	α	β
All	Pr.comp. 1	8.721	0.317 **	0.000
	Pr.comp. 2	2.493	0.215 **	0.644 **
	Pr.comp. 3	19.414	0.262 **	0.000
	Pr.comp. 4	71.237	0.164 **	0.758 **
Countries only	Pr.comp. 1	12.130	0.140 **	0.189
	Pr.comp. 2	18.267	0.221 **	0.000
	Pr.comp. 3	35.712	0.164 **	0.756 **
Industries only	Pr.comp. 1	3.723 **	0.440 **	0.000
	Pr.comp. 2	36.729	0.181 **	0.744 **

discussed in this section with care. The statistics of the minimum variance portfolio (MVP) and the Sharpe ratio for all investment categories and all three robustness tests are presented in Table 2.3. Looking at Table 2.3 we see that excluding some of the possible indices had an influence on the performance. Especially in the case of excluding 2 out of 10 industry indices it makes sense that the Sharpe ratio should decline. However, our main conclusions are still valid. Even in the case where we compare investing in all country indices with investing in only 5 industry indices (Figure 2.6), still, the better diversification opportunities can be found by diversifying over industries. This evidence suggests that the rise in the technology markets has only strengthened the trend of more important industry factors. These robustness tests also show that diversifying over both categories remains the best strategy.

Figure 2.7
The conditional volatilities of the principal components

When both types of indices are considered, the test for conditional heteroskedasticity is rejected in four (out of 21) cases. A GARCH(1,1) model is estimated for these principle components. This figure shows the four resulting conditional volatilities.



2.4.3 Robustness with respect to differences in volatility

The second test we perform, deals with the robustness of our results with respect to different volatility regimes. For that purpose we use the O-GARCH methodology as described in section 2.2.3, which is a possible multivariate parameterization of a model with GARCH-components. Basically, the method identifies the principal components of the stock indices. For each component we test for the presence of heteroskedasticity and estimate a GARCH(1,1) process if this is the case.

This procedure is followed three times: for country indices only, for industry indices only and for both types of indices simultaneously. Table 2.4 gives the estimates of the GARCH-parameters for all the principles components that contained conditional heteroskedasticity. The table shows that the number of components for which the null hypothesis of no heteroskedasticity is rejected is relatively low: 4, 3 and 2 for all indices, only country indices or only industry indices respectively. The variances of all other components are constant over time and do not play an important role for this robustness test.

The conditional volatilities are plotted in Figure 2.7. For sake of brevity we only plotted the time-varying volatilities of the principle components when we consider both types of investments simultaneously. Figure 2.7 shows that there is quite some substantial variation in the conditional volatilities. Hence, we want to check whether our conclusions are valid for all possible volatility regimes. In order to check this we consider the efficient frontiers based on two different periods: a period with a relatively high volatility and a period with a relatively low volatility. In general, the volatilities seem to be high around the introduction of the euro. Therefore, we chose December 1998 as the high volatility period. Two years later the average volatility seems to have hit a low: December 2000 is taken as the low volatility period.

Figures 2.8 and 2.9 present the efficient frontiers based on the conditional covariance matrix (resulting from the O-GARCH methodology) for the high and the low volatility period respectively. These pictures show that our conclusions are also robust over different volatility regimes. Although the differences are less pronounced when the volatility is low, a portfolio based on industry indices clearly has a better mean-variance ratio than a portfolio based on country indices in both periods considered. The only noticeable difference is the higher (lower) portfolio variance, which can be deduced from the shift of the whole efficient frontier to the right (left). The efficient frontiers based on the last conditional covariance matrix in our sample, thereby including all information (see Figure 2.10), also shows similar patterns amongst the frontiers.

Figure 2.8
Conditional efficient frontiers with the covariance matrix based on 98:12

This figure plots the conditional mean-variance frontiers on a specific time period in the sample. The frontiers are based on the mean return of the whole sample and the conditional covariance matrix of December 1998. The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.

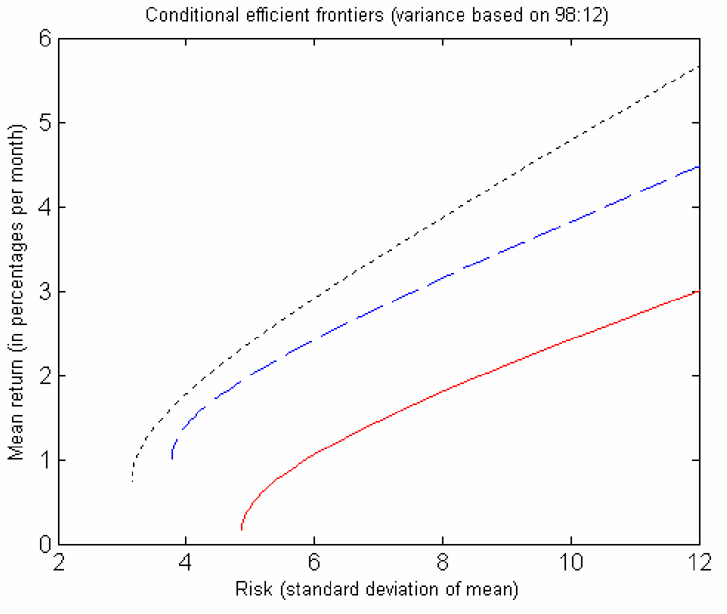


Figure 2.9
Conditional efficient frontiers with the covariance matrix based on 00:12

This figure plots the conditional mean-variance frontiers on a specific time period in the sample. The frontiers are based on the mean return of the whole sample and the conditional covariance matrix of December 2000. The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.

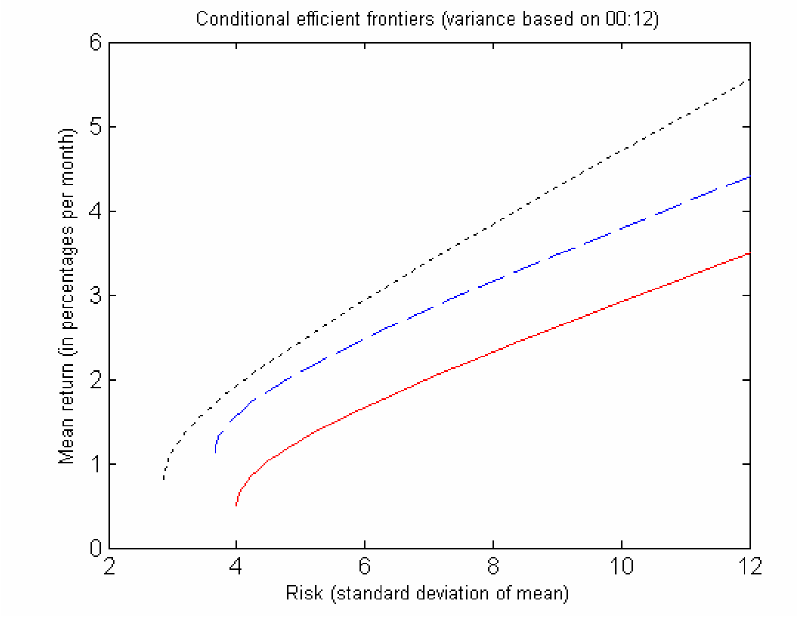


Figure 2.10

Conditional efficient frontiers with the covariance matrix based on 02:10

This figure plots the conditional mean-variance frontiers on a specific time period in the sample. The frontiers are based on the mean return of the whole sample and the conditional covariance matrix of October 2002 (last month in the sample). The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices.

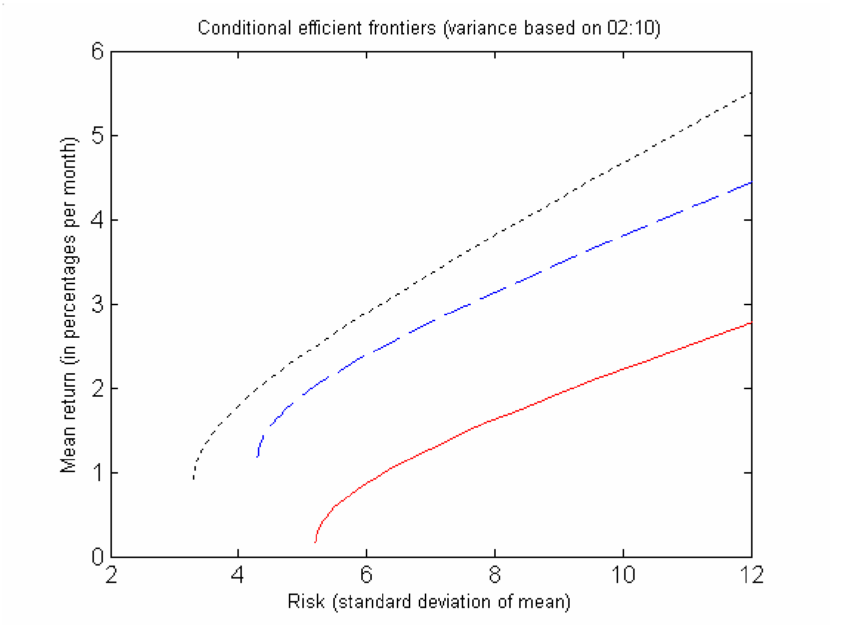
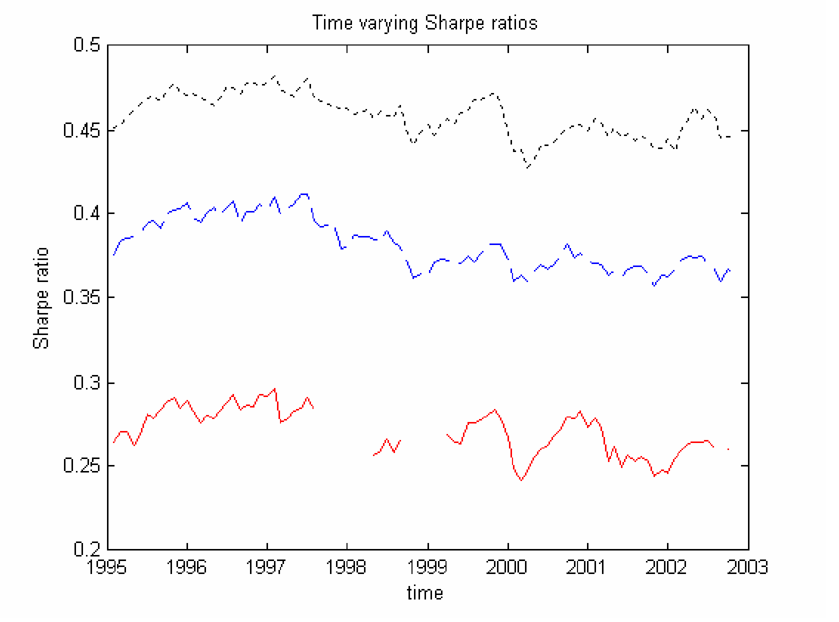


Figure 2.11
Time varying Sharpe ratios

This figure plots the Sharpe ratios for each month in the sample based on the estimate of the conditional covariance matrix of that period. The solid line represents all investment possibilities when only country indices are considered. The dashed line is the mean-variance frontier for the industry indices. The dotted line considers both types of indices. In case only country indices were considered the Sharpe ratio became negative in a few instances. These observations are not plotted.



An alternative way of presenting the time variability in the mean-variance frontiers is by looking at the Sharpe ratio. The O-GARCH methodology allows us to calculate this ratio for each time period in the sample. The changes in the Sharpe ratios over time are depicted in Figure 2.11. Again, the same conclusions can be drawn from this picture. Next to that, the figure also shows that the time variability based on conditional second moments is not extreme. In future research we would like to take this into account and extend the research with conditional expected returns. Overall, the results of this section support our conclusions and show that an investor in the euro area stock markets cannot neglect industry factors.

2.5 Conclusions

The ongoing process of integration within the European Union and the euro area in particular is the subject of much debate. Due to the harmonization of monetary and policy rules, most notably the introduction of the euro per January 1st 1999, European financial markets are becoming more correlated with each other (see e.g. Adjaouté and Danthine, 2002; Hardouvelis, Malliaropoulos and Priestley, 1999). This chapter deals with the consequences of these changes on the diversification opportunities within the euro-zone. Special attention is paid to the difference between country and industry effects. Several papers that cover this subject (Roll, 1992; Heston and Rouwenhorst, 1994, 1995; Griffin and Karolyi, 1998; Rouwenhorst, 1999) document that country effects are more prevalent than industry effects. Recent research (Cavaglia, Brightman and Aked, 2000; Isakov and Sonney, 2002) reports that country effects are losing field, which can partly be explained by the IT-hype during the late 90's (Brooks and Del Negro, 2004). Furthermore, there is criticism on the restrictive Heston and Rouwenhorst (1994, 1995) methodology (Adjaouté and Danthine, 2002; Brooks and Del Negro, 2002). In this chapter we revisit the issue for the euro area stock markets and with a different approach we show that industries are more important than countries with respect to diversification opportunities.

We plot the mean-variance frontiers of three investment policies (country indices only, industry indices only and both types of indices) for different samples. Our conjecture, that the performance of a pure country investment strategy is decreasing as a result of the European integration process, is supported by the results in this chapter. The unconditional analysis until January 1999 shows that an industry strategy gave similar results as a country strategy. Using more recent samples we report evidence that the diversification opportunities between countries have been decreasing. In the most recent samples or based on the recent conditional covariance matrix it is clear that diversifying over industries is a much better strategy than diversifying over countries. Unsurprisingly, the best portfolio can be constructed when the investor considers both categories simultaneously, suggesting that country specific factors still play at least some role in the determination of stock returns and their correlation across euro area stock markets. Concluding, given our methodology, the traditional top-down allocation scheme, where it is first decided how to divide the money over several countries and secondly how to spread the investments within a country, seems to be outdated for the euro area stock markets. This contrasts with the results of Rouwenhorst (1999), but is in line with Cavaglia, Brightman and Aked (2000) and Isakov and Sonney (2002). They report a rising trend in the relative importance of industry factors. Our results suggest that this trend is moving forward.

We argue that our conclusions are an outcome of the European integration process. However, the results might be driven by the extreme performance of IT-stocks around the turn of the century, which roughly coincides with the introduction of the euro.

Brooks and Del Negro (2004) find that the level of industry effects decreases on a global scale after correcting for the IT-hype. We show that our conclusions remain valid after excluding indices with a large information technology component and that the industry effect only strengthened the IT-hype. Therefore, we attribute the change in the relative importance of industry factors to the European integration process.

Chapter 3

How Domestic is the Fama and French Three-Factor Model? An Application to the Euro Area

3.1 Introduction

Since the introduction of the CAPM by Sharpe (1964) and its extension by Lintner (1965) asset pricing models have been an intensive topic of research. In a fully integrated market where purchasing power parity (PPP) holds, the global CAPM should price all assets (see Grauer, Litzenberger and Stehle, 1976). However, many studies show that PPP usually doesn't hold[16]. In that case, a correct specification of an asset-pricing model should entail exchange rate risk factors. Such international asset pricing models are developed by Solnik (1974), Sercu (1980), Stulz (1981) and Adler and Dumas (1983).[17]

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[16] See e.g. Abuaf and Jorion (1990), Froot and Rogoff (1995), Chinn (2002), Koedijk, Tims and van Dijk (2004)

[17] Stulz (1995) gives a comprehensive review of the literature on the different asset pricing models.

Another extension of the CAPM was suggested by Fama and French (1992, 1993, 1995, 1996). Besides the world market factor they included two zero-cost portfolios: a Small minus Big (SMB) portfolio based on the total market capitalization of the firms considered and a High-minus-Low (HML) portfolio which is based on the book-to-market value of the stock. In their studies Fama and French show that their asset-pricing model performs better than the traditional CAPM. In a later study (Fama and French, 1998), they provide the international evidence by investigating the model for a number of countries. Despite the good performance of their model several studies question their methodology. Daniel and Titman (1997) find that rather the characteristics than the covariance structure of the returns explains the cross-sectional variance of the stock returns. Other studies (Campbell (1996), Ferson and Harvey (1999) and Lettau and Ludvigson (2001)) show that incorporating conditioning information in a traditional CAPM also increases the ability to explain the returns.

In this chapter we do not contribute to the methodological discussion, but try to answer a more practical question. Although Fama and French (1998) advocate a global version of their model, many practitioners and academics use a local version of the three-factor model in order to make correct estimates of the expected stock returns (e.g. for portfolio selection problems and cost-of-capital calculations[18]). Griffin (2002) documents that a local three-factor model is better (in terms of adjusted R^2 and Jensen's alpha) than the global version for the stock markets of the U.S., Canada, the U.K., and Japan. The result is found for both portfolios and individual securities and is also robust for basic methodological changes.

We address the same issue for the euro area. Although not all countries are as integrated with the world market as the four large countries mentioned above, the euro area forms a very integrated area by itself.[19] Over the last decade a number of changes in the European Monetary Union have had a big influence. Besides the harmonization of monetary and policy rules and legislation, the playing field for institutional investors (the largest investors in the European market) changed considerably.[20] During our sample period the restriction on maximum investments in stocks has been relieved and the introduction of the common currency opened up the euro area market for the institutional investors even more. Consequently, the termination of the exchange rate risk within the

[18] See amongst others Stulz(1998), Koedijk, Kool, Schotman and van Dijk (2002) and Karolyi and Stulz (2002) for discussions on the local versus global (I)CAPM, e.g.. for cost of capital calculations.
[19] Hardouvelis, Malliaropoulos and Priestley (1999) show using a conditional framework that most member states of the European Monetary Union seem to become fully integrated with each other in 1997.
[20] Institutional investors are usually very restricted concerning investments in stock markets, both in the maximum amount invested (in percentages of total assets) and how these investment are allowed to vary over different stock markets (it is very common that the greater part has to be invested in local currency-denominated markets).

euro area spurred the (financial) integration process amongst these countries.[21] Given these changes and the resulting union, it is interesting to see what factors drive the stock markets in this area. As discussed above, Griffin (2002) shows that the domestic model is preferred, but which "domestic model" applies to the euro area? Are asset prices driven by local country factors or are euro area factors more appropriate nowadays. In this chapter we address this issue and examine the behavior of these asset-pricing markets over time as well.

We study the equity markets of all euro-participating countries over the period 1991:07 until 2002:08. We create portfolios for each country based on the book-to-market and the size characteristics of the companies considered. The returns of these portfolios are used to test the different asset pricing models. We find that the domestic three-factor model (country 3FM) clearly outperforms the euro area three-factor model. Given the European integration during our sample (as evidenced by Hardouvelis, Malliaropoulos and Priestley, 1999), we split the sample in two parts to examine the behavior of the asset pricing models in each sub period. We show that the difference in the first part of the sample is substantial (the mean absolute pricing error of the country 3FM is up to 40% lower than the pricing error of the euro area 3FM). In the second sub sample this difference decreases to approximately 7%. Thus, even though the (relative) performance of the euro area model has increased substantially, the country 3FM still produces the lowest pricing errors on average.

Furthermore, we also group the stocks along another dimension. Among others, Fama and French (1997) show that pricing industry portfolios is very difficult. However, no studies (to the author's knowledge) have implemented an industry-specific three-factor model (industry 3FM) following the Fama-French methodology. In this chapter we address this issue and compare the results with the euro area 3FM. For each sector we create a number of portfolios based on the book-to-market or size characteristics of the firms. As in the country case, we find that an industry 3FM clearly outperforms the euro area 3FM. This result is robust over the sub periods and holds for both book-to-market and size-sorted portfolios.

The rest of the chapter is organized as follows. Section 3.2 provides the methodology used in this chapter. Section 3.3 discusses the data used and explains how the portfolios are constructed. Section 3.4 presents the results and section 3.5 concludes.

[21] Recent studies, that consider the euro area asset markets in particular, find that the changing environment of the euro area is slowly reflected in the financial markets (see e.g. Cavaglia, Brightman and Aked, 2000; Isakov and Sonney, 2002).

3.2 Methodology

We estimate different versions of the Fama and French three-factor model (3FM). We employ the same methodology and same performance measures as Griffin (2002) and apply this approach to the euro area stock markets. This section covers the applied models in more detail.

The 3FM relates the expected return on a stock or portfolio in excess of the risk free rate to three different factors: (1) the excess return of the market portfolio; (2) the difference between the return on a portfolio of small market capitalization stocks and the return on a portfolio of big capitalization stocks (SMB, small minus big); (3) the difference between the return on a portfolio of high book-to-market stocks and the return on low book-to-market stocks (HML, high minus low), which proxies the value or distress premium. In a regression framework this model can be written as:

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot [R_{mt} - R_{ft}] + s_i \cdot SMB_t + h_i \cdot HML_t + \varepsilon_{it} \qquad \textbf{(3.1)}$$

where R_{it}, R_{ft} and R_{mt} are respectively the return on a stock or portfolio, the risk-free rate and the market return; β_i, s_i and h_i are the unconditional sensitivities of the i^{th} asset for the specific factors, α_i is the pricing error and ε_{it} the error term.

In this chapter we focus on the domestic 3FM of Fama & French applied to the euro area (or European Monetary Union). The main research question covered in this chapter answers how *domestic* these factors (market return, SMB, HML) should be. A natural definition of domestic factors is country-specific factors. However, given the rate of integration and the introduction of the common currency in the European Monetary Union, a 3FM with euro-area-based factors could also be seen as a domestic model. In section 3.2.1 we discuss both of these models and examine which model produces the lowest pricing errors. Instead of using geographical characteristics in defining the 'local factors', one can also create factors for each different sector. As discussed in the introduction, the regulatory changes in Europe have been numerous and consequently investors should take a sector-based approach in examining the euro area capital markets.[22] Following these lines an industry-based 3FM is perfectly rational. Furthermore, these analyses can bring new insights in the discussion on pricing industry portfolios (which is very hard according to e.g. Fama and French, 1997). The methodology for the industry-based factor models is discussed in section 3.2.2.

[22] See e.g. Cavaglia, Brightman and Aked (2000), Rouwenhorst (1999), Isakov and Sonney (2002) and

3.2.1 Euro area vs. the country three-factor model

In a fully integrated market there is only one set of factors that prices all assets of each country. Assuming that the euro area is a highly integrated area, we can define the euro area three-factor regression model (euro area-3FM) as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot EMRF_t + s_i \cdot ESMB_t + h_i \cdot EHML_t + \varepsilon_{it} \quad \textbf{(3.2)}$$

where $EMRF_t$ is the euro area market excess return, $ESMB_t$ represents the small minus big portfolios for the euro area and $EHML_t$ is the euro area high minus low portfolio. For the definition of the EMU risk factors, we follow the methodology of Griffin (2002), who defines the global risk factors as the weighted averages of all domestic risk factors under consideration.

$$EMRF_t = w_{Dt-1} \cdot DMRF_t + w_{Ft-1} \cdot FMRF_t \quad \textbf{(3.3)}$$

where $DMRF_t$ and $FMRF_t$ are the domestic excess market return and the foreign excess market return respectively; the weight w_{Dt-1} is equal to the country's total market capitalization in the previous month over the total EMU market capitalization in the previous month and w_{Ft-1} is the weight for all foreign countries and by definition the complement of w_{Dt-1}. The other two factors ($ESMB_t$ and $EHML_t$) are defined in a similar way.

The three-factor model described in equation (3.2) restricts the domestic and the foreign factors to have the same impact on stock returns. If one allows the foreign factors to have a different influence on the returns, the following international country factor model regression can be defined:

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i &+ \beta_{Di} \cdot (w_{Dt-1} \cdot DMRF_t) + s_{Di} \cdot (w_{Dt-1} \cdot DSMB_t) + h_{Di} \cdot (w_{Dt-1} \cdot DHML_t) \\ &+ \beta_{Fi} \cdot (w_{Ft-1} \cdot FMRF_t) + s_{Fi} \cdot (w_{Ft-1} \cdot FSMB_t) + h_{Fi} \cdot (w_{Ft-1} \cdot FHML_t) + \varepsilon_{it} \end{aligned} \quad \textbf{(3.4)}$$

We will refer to this as the international country 3FM. It is formed by decomposing the global model into the specific domestic-related components and foreign country components.[23] If the foreign factors are irrelevant, the international country 3FM collapses to the country 3FM:

$$R_{it} - R_{ft} = \alpha_i + \beta_{Di} \cdot DMRF_t + s_{Di} \cdot DSMB_t + h_{Di} \cdot DHML_t + \varepsilon_{it} \quad \textbf{(3.5)}$$

In order to assess the performance of the three different models considered we apply two separate performance measures. First of all, the adjusted R^2s of the different

[23] In case of highly integrated markets, this specification is not identified. The factor-pairs (e.g. DMRF and FMRF) are then highly correlated. We will therefore not pay a lot of attention to this model, but do report the results in order to be able to compare them with Griffin (2002).

regressions are compared. Although the R^2 rises when useful factors are added, it is not the best statistic to compare models. A more reliable performance measure is the pricing error of the regression (α_i). On average, the most effective model is best able to price (portfolios of) assets and hence produces a lower pricing error (in absolute terms). The models are tested on different groups of portfolios. Following the literature we will mainly focus on BE/ME-sorted portfolios and on size-sorted portfolios.

3.2.2 The industry asset pricing model

This section covers another possible avenue for a "domestic model". Instead of defining a local asset pricing factor model for each country, we also consider asset-pricing models for each industry category. As mentioned before, the European (Monetary) Union is in the middle of an integration process. Given this dynamic environment many studies have been done in order to test for structural changes in the European financial markets. Some of these studies argue that industry factors are becoming more important relative to country factors (see footnote 5). From this point of view an industry asset pricing model is an interesting topic of research. Furthermore, it is well known that industry portfolios are hard to price using the normal CAPM or 3FM.[24] The rest of this section discusses the methodology used for this model.[25]

For every industry we create an industry return, a SMB portfolio and a HML portfolio. Thus, we can now split up the euro area 3FM (as in equation (3.2)) into an international industry model:

$$\begin{aligned} R_{it} - R_{ft} &= \alpha_i + \beta_{Ii} \cdot (w_{It-1} \cdot IMRF_t) + s_{Ii} \cdot (w_{It-1} \cdot ISMB_t) + h_{Ii} \cdot (w_{It-1} \cdot IHML_t) \\ &\quad + \beta_{Oi} \cdot (w_{O,t-1} \cdot OMRF_t) + s_{Oi} \cdot (w_{Ot-1} \cdot OSMB_t) + h_{Oi} \cdot (w_{Ot-1} \cdot OHML_t) + \varepsilon_{it} \end{aligned} \quad \textbf{(3.6)}$$

where $IMRF_t$, $ISMB_t$ and $IHML_t$ are the factors for a specific industry and $OMRF_t$, $OSMB_t$ and $OHML_t$ are the risk factors for the other industries. The model is similar to the international country model with the exception that the factors are now industry-based. The parameterization allows us to check which factors are the most important in explaining the cross-section of returns. In case the factors of the other sectors are irrelevant, the international industry model collapses to the industry 3FM:

$$R_{it} - R_{ft} = \alpha_i + \beta_{Ii} \cdot IMRF_t + s_{Ii} \cdot ISMB_t + h_{Ii} \cdot IHML_t + \varepsilon_{it} \quad \textbf{(3.7)}$$

[24] See, amongst others, Fama and French (1997), Hussain, Diacon and Toms (2002), Van Vliet and Post (2004).
[25] To our knowledge, the industrial Fama & French model has not been a topic of research yet. Hussain & Toms (2002) study a related topic. They consider industry portfolios and regress these on the standard (domestic) risk factors for the UK. However, the risk factors are still country-based and not industry based.

Table 3.1
Industry classification codes

This table displays the FTSE-industry codes. This industry-categorization is used to divide all assets in industry specific portfolios.

	INDC3	Definitions
00	Resor	Resources
10	Basic	Basic Industries
20	Genin	General Industries
30	Cycgd	Cyclical Consumer Goods
40	Ncyg4	Non-Cyclical Consumer Goods
50	Cyser	Cyclical Services
60	Ncysr	Non-Cyclical Services
70	Utils	Utilities
80	Totlf	Financials
90	Itech	Information Technology

We use BE/ME-sorted and size-sorted industry portfolios for testing the different asset pricing models. The performance criteria used for the comparison are the same as mentioned above: the (absolute) pricing error (α_i's) and the adjusted R^2s.

Unfortunately, we cannot compare the country and industry model directly, since they are not nested. Moreover, there is a slight difference between the two European models, which comes from the methodological assumptions that we make (following Griffin, 2002). Appendix A discusses this in more detail. Furthermore, we tested an alternative specification where the European models are exactly the same, but this doesn't give major changes for our results.[26]

3.3 Data

We apply our methodology to stocks from the euro-participating countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain. Luxembourg is the twelfth country that belongs to the euro area, but it is usually ignored in this type of studies because of the small number of stocks in this country. The monthly stock returns (including dividends and capital gains) are downloaded from

[26] The results of this model are available upon request from the author.

Datastream[27]. For each asset we also retrieve the FTSE industry classification (see Table 3.1 for the different classifications), market capitalization and the book-to-market (BE/ME) ratio for each month. As a conditionally risk-free asset we use the return on the one-month euro-mark deposit quoted in London (also extracted from Datastream). All asset returns (before the introduction of the common currency) are translated into Deutsche marks using the bilateral exchange rates.[28] The monthly excess returns are computed by subtracting the risk-free rate from the monthly return of each security. Table 3.2 presents the summary statistics for the country market indices that are constructed based on the assets that fulfill the criteria. Panel B of this table reports the unconditional correlations between the several indices. The indices are clearly correlated with each other and most country indices are very highly correlated with the euro area index.

The biggest difference of European data versus US data concerns the number of stocks. This holds especially for this study, since we investigate a domestic 3FM for each country (and for each industry). Table 3.3 shows the number of stocks that are used for the creation of the different factors at the beginning of July for each year. This number can decline throughout the year, because of mergers, takeovers, bankruptcies or any other reason of delisting. Considering Table 3.3 we see that there are huge differences between the European countries and industries. Germany and France are the largest countries with approximately 200 listed stocks, while Ireland and Greece are the smallest countries with less than 20 stocks in the beginning of the sample. The same holds for the different sectors that we consider. There are big differences in the number of stocks of different industries, ranging from less than 20 for the Information Technology sector in the first four years of our sample to almost 250 in some years for the Financials. We will take this into account during the interpretation of the results by presenting our results both for the whole euro area as well as for the bigger countries/industries only.

The sample runs from July 1991 till August 2002. Although this is a fairly short sample for this type of studies, we chose to stick to recent data only. The reasons for this choice are twofold. First, a much longer time series would lower the listed stocks per country even more. Secondly, the local versus global discussion on the Fama and French 3FM is based on the assumption of market integration. Although one can argue that the markets in the beginning of our sample might not be fully integrated, Hardouvelis, Malliaropulos and Priestley (2001) find that most of these markets do around 1998. Hence,

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[27] For each country we selected the stocks that are listed in the Datastream total market index of the countries under consideration. These indices cover 80% of all available stocks, which suggests that it covers more than 99% of the market capitalization of each country. The delisted stocks are taken from the Datastream dead stocks lists.

[28] The same holds for the market value and the book-to-market ratio. In order to make a smooth transition to the euro-nominated returns, we multiplied all values with the irrevocable exchange rate, which is available at: European Central Bank, http://www.ecb.int (accessed 3 October, 2003)

Table 3.2.
Summary Statistics

This table reports the summary statistics on the market indices used in the analysis. The indices are constructed using all available stocks from Datastream that fulfill the criteria (see section 3.4.3). Panel A presents the summary statistics and **, *** used for the Jarque-Bera statistic denote significance at the 5% and 1% significance levels respectively. Panel B reports the unconditional correlations between the market indices.

	Euro area index	**Germany**	**Belgium**	**Spain**	**Finland**	**France**	**Greece**	**Ireland**	**Italy**	**Netherlands**	**Austria**	**Portugal**
Panel A: Summary Statistics of all market indices												
Mean	0.515	0.319	0.507	0.543	1.171	0.481	0.766	0.693	0.797	0.684	-0.166	0.341
Median	0.401	0.759	0.582	0.311	1.094	0.650	-0.617	1.453	-0.247	1.014	0.288	-0.097
Standard dev.	5.055	5.311	4.597	6.314	10.512	5.447	9.209	6.047	8.287	5.171	5.308	6.014
Skewness	-0.394	-0.532	-0.604	-0.076	0.345	-0.280	0.550	-0.790	0.933	-0.935	-0.403	0.856
Kurtosis	3.772	3.512	4.360	4.545	4.308	3.917	4.440	4.432	4.922	5.485	4.235	8.089
Jarque-Bera	6.79 **	7.78 **	18.5 ***	13.5 ***	12.2 ***	6.45 **	18.3 ***	25.4 ***	40.1 ***	54.0 ***	12.1 ***	161 ***
Panel B: Unconditional correlations between the market indices												
Euro area index	1											
Germany	0.927	1										
Belgium	0.753	0.685	1									
Spain	0.826	0.720	0.684	1								
Finland	0.704	0.634	0.389	0.494	1							
France	0.930	0.837	0.687	0.755	0.609	1						
Greece	0.503	0.492	0.420	0.437	0.348	0.476	1					
Ireland	0.652	0.614	0.625	0.640	0.472	0.567	0.406	1				
Italy	0.705	0.532	0.464	0.614	0.494	0.534	0.263	0.363	1			
Netherlands	0.895	0.845	0.780	0.742	0.614	0.822	0.427	0.678	0.480	1		
Austria	0.616	0.615	0.611	0.542	0.343	0.549	0.379	0.392	0.379	0.610	1	
Portugal	0.700	0.614	0.499	0.661	0.430	0.691	0.379	0.439	0.466	0.597	0.477	1

the start of the sample is a consideration between more available data versus complying with the null hypothesis of integrated markets.

For the construction of the risk factors we follow Griffin (2002) by applying the Fama and French (1992, 1993, 1996) methodology. For stocks to be included in the analysis the firm must have a stock price for June of year t. Furthermore, the firm should have a market value for June of year t and a book-to-market value for December of year t-1. Firms that have a negative book-to-market value on December of year t-1 are not included in the sample. This selection procedure is used for all stocks in the DataStream total market index. Given this selection of firms, in June of year t all stocks are ranked on size. The sample is then split using the median market capitalization of all firms of a country (or industry) into a small (S) and a big (B) portfolio. The stocks are also ranked on their book-to-market equity of December of year t-1. For the book-to-market classification, the bottom 30% are classified as low book-to-market firms (L), the middle 40% into the middle (M) portfolio and the top 30% as high book-to-market firms (H). Using the intersection of these independent stock splits we can construct six portfolios: BH, BM, BL, SH, SM and SL. The SMB-portfolio is defined as the simple average of all small-stock portfolio returns minus all big stock portfolio returns, or SMB= (SH + SM + SL - BH – BM – BL)/3 for each month. The HML portfolio is the simple average of all high BE/ME stock portfolio returns minus all low stock portfolio returns, or HML= (SH + BH – SL – BL)/2 for each month[29].

The test assets are in line with the existing literature. We create portfolios based on the ranking of the assets on the BE/ME-ratio or on size. The number of tested portfolios is varied, changing from 3 to 6 and 10. By this variation we can test the robustness of our results. However, we should note again that the number of stocks is limited for the smaller European countries: the larger the number of portfolios, the less stocks that are on average in a portfolio. For example, in the beginning of the sample Greece only contained eleven stocks. When these are divided over 10 portfolios, it means that 9 out of 10 portfolios only contain one stock! For completeness, we apply our methodology on all euro-participating countries, but we will check the robustness of the results with respect to the inclusion of these smaller countries or industries.

[29] In the case of Ireland and Greece, the middle book-to-market portfolio does not exist. Because of the limited number of stocks in the beginning of the sample, we decided to split the sample into two book-to-market portfolios.

Table 3.3
Number of stocks

This table reports the number of stocks that meet the criteria. The asset must have a listed price for June of that respective year, the market value in June should be known and the book-to-market ratio for December of the previous year should also be available. Following the standard Fama and French methodology we find the following number of stocks for the month of June of that year. The number of stocks changes a lot over time due to new issues, mergers, takeovers and bankruptcies. The Fama and French portfolios are updated in June each year and therefore this table reports the number for that month. Due to delistings the number of stocks per country and for some portfolios might decline over the year. The addition of stocks only occurs in June of the following year, when the new portfolios are constructed. Panel A contains the numbers over the different countries included and Panel B covers the same statistic for the different industries.

PANEL A: THE NUMBER OF STOCKS PER COUNTRY FOR EACH YEAR

Country	**91**	**92**	**93**	**94**	**95**	**96**	**97**	**98**	**99**	**00**	**01**	**02**
Germany (BD)	177	191	204	211	220	227	211	210	197	215	209	198
Belgium (BG)	46	45	47	51	50	47	50	43	41	38	33	32
Spain (ES)	48	55	64	66	69	72	97	107	108	111	102	101
Finland (FN)	32	34	36	38	56	60	65	66	63	57	53	46
France (FR)	253	253	258	268	266	263	253	247	221	197	177	170
Greece (GR)	11	17	22	24	28	31	42	41	45	50	56	45
Ireland (IR)	15	16	16	17	17	17	18	20	34	36	35	31
Italy (IT)	77	83	90	91	102	114	120	126	132	129	121	111
Netherlands (NL)	149	150	144	142	141	136	138	144	142	124	104	90
Austria (OE)	35	38	40	47	58	64	68	66	57	55	50	47
Portugal (PT)	33	34	42	43	47	45	49	54	54	46	40	41
Total	876	916	963	998	1054	1076	1111	1124	1094	1058	980	912

PANEL B: THE NUMBER OF STOCKS PER INDUSTRY FOR EACH YEAR

Sector		**91**	**92**	**93**	**94**	**95**	**96**	**97**	**98**	**99**	**00**	**01**	**02**
00	Resor	59	55	50	54	54	46	45	41	33	25	23	20
10	Basic	138	140	145	154	165	174	184	184	182	165	158	151
20	Genin	152	155	155	160	170	168	166	154	150	141	127	110
30	Cycgd	84	89	90	96	99	104	106	113	109	106	96	88
40	Ncyg4	89	101	103	104	112	120	111	119	122	117	105	100
50	Cyser	105	106	107	109	121	125	136	146	147	145	145	140
60	Ncysr	39	43	48	46	45	44	46	45	42	44	37	36
70	Utils	33	35	35	36	37	37	37	39	41	38	37	33
80	Totlf	159	174	212	221	230	232	251	251	230	222	196	180
90	Itech	18	18	18	18	21	26	29	32	38	55	56	54
	Total	876	916	963	998	1054	1076	1111	1124	1094	1058	980	912

3.4 Results

We use the same performance criteria for measuring the performance of the different asset pricing models as Griffin (2002). The first criterion is the pricing error, also called Jensen's alpha. Under the null hypothesis that the factor model is indeed the data generating process, the predicted value of alpha in the estimated equation should be equal to zero (see equation (3.2), (3.4) and (3.5) for the European, the international or the domestic model respectively). The estimated value of alpha then gives the pricing error of the asset-pricing model under consideration. For each group of assets we report the mean absolute pricing error.[30] The second criterion is the average adjusted R-squared, which is the explanatory power of the regression.

3.4.1 The country vs. the euro area 3FM

For every country in our sample we regress the time series of returns of the different book-to-market sorted portfolios on three versions of the 3FM: the euro area 3FM, the international country 3FM and the (local) country 3FM (see equations (3.2), (3.4) and (3.5)). The results are summarized in the Table 3.4. The first three rows cover the average results. The following three rows contain the same results but only concerning the bigger countries (Germany, France, Italy and the Netherlands), while the rest of the table presents the performance measures for each country separately.

For example, when the stocks are divided into three book-to-market sorted portfolios we find that the euro area 3FM performs worse than the other two models based on both performance criteria. The mean absolute pricing error for the euro area 3FM (0.449) is more than double compared to the international model (0.191) or the domestic model (0.189). The adjusted R^2 of the euro area 3FM (0.482) is also substantially lower than 0.859 and 0.851 of the international and the domestic asset-pricing model respectively. The results stated in the second and third row represent the cases where the number of portfolios is increased to six or ten. The overall performance of the asset pricing models declines (the mean absolute pricing errors rise, while the R^2s drop), but the relative conclusions stay the same: both the domestic 3FM and the international country 3FM are clearly better in explaining the cross-section of stock returns than the euro area 3FM is.

[30] One can also test the pricing errors using the statistical procedures as proposed by Gibbons, Ross and Shanken (1989). These tests showed that most pricing models didn't have significant alpha's. This is partly caused by the fact that our sample period is relatively short and the Gibbons-Ross-Shanken-test only holds asymptotically under normally distributed errors. Furthermore, the results are very similar to the mean absolute pricing error criterion. Since this last criterion is more relevant in economic terms, we chose to only report the results on the absolute pricing errors.

Table 3.4

Country vs. euro area model, book-to-market sorted portfolios, full sample

This table presents the two performance measures resulting from regressing the book-to-market sorted portfolios of the countries considered using the full sample on three different asset pricing models: the euro area 3FM, the international country 3FM and the country 3FM (see equation (3.2), (3.4) and (3.5) respectively). For each model the mean absolute pricing error is stated in the first column of the model and the second column contains the average adjusted R^2. The top rows depict the averages of the performance measures for all countries and the three following rows average over the four largest countries (France, Germany, Italy and the Netherlands).

The number of portfolios and Country considered	European model		International model		Country model	
	Av. $\|\alpha\|$	Av. R^2	Av. $\|\alpha\|$	Av. R^2	Av. $\|\alpha\|$	Av. R^2
Average, 3	0.449	0.482	0.191	0.859	0.189	0.855
Average, 6	0.428	0.424	0.289	0.737	0.286	0.730
Average, 10	0.483	0.366	0.365	0.628	0.343	0.620
(only big countr.) 3	0.324	0.657	0.181	0.891	0.210	0.887
(only big countr.) 6	0.309	0.590	0.289	0.788	0.270	0.782
(only big countr.) 10	0.336	0.530	0.276	0.709	0.250	0.701
Germany 3	0.309	0.730	0.292	0.880	0.315	0.881
Germany 6	0.239	0.663	0.242	0.795	0.249	0.795
Germany 10	0.233	0.591	0.198	0.713	0.175	0.702
Belgium 3	0.293	0.510	0.022	0.850	0.048	0.850
Belgium 6	0.230	0.423	0.214	0.686	0.242	0.686
Belgium 10	0.402	0.349	0.326	0.565	0.378	0.563
Spain 3	0.185	0.544	0.247	0.854	0.227	0.844
Spain 6	0.252	0.487	0.350	0.770	0.382	0.761
Spain 10	0.324	0.434	0.383	0.672	0.427	0.664
Finland 3	0.718	0.400	0.392	0.825	0.177	0.807
Finland 6	0.697	0.339	0.385	0.682	0.271	0.663
Finland 10	0.692	0.285	0.492	0.575	0.355	0.554
France 3	0.229	0.775	0.217	0.904	0.273	0.903
France 6	0.294	0.684	0.316	0.804	0.338	0.802
France 10	0.289	0.622	0.288	0.734	0.333	0.727
Greece 3	0.579	0.214	0.363	0.907	0.387	0.908
Greece 6	0.586	0.176	0.439	0.792	0.453	0.791
Greece 10	0.749	0.150	0.614	0.680	0.589	0.680
Ireland 3	0.761	0.270	0.211	0.710	0.269	0.707
Ireland 6	0.602	0.247	0.154	0.570	0.304	0.547
Ireland 10	0.558	0.169	0.419	0.393	0.475	0.374
Italy 3	0.330	0.508	0.098	0.916	0.124	0.914
Italy 6	0.360	0.493	0.239	0.857	0.167	0.852
Italy 10	0.400	0.467	0.297	0.794	0.201	0.789
Netherlands 3	0.427	0.616	0.116	0.866	0.127	0.851
Netherlands 6	0.342	0.519	0.361	0.696	0.326	0.679
Netherlands 10	0.423	0.439	0.323	0.596	0.293	0.584
Austria 3	0.885	0.372	0.046	0.901	0.094	0.902
Austria 6	0.830	0.301	0.243	0.732	0.239	0.734
Austria 10	0.852	0.258	0.334	0.619	0.283	0.612
Portugal 3	0.226	0.363	0.096	0.835	0.040	0.836
Portugal 6	0.278	0.336	0.240	0.726	0.173	0.722
Portugal 10	0.390	0.262	0.342	0.571	0.262	0.569

This result is robust over the number of portfolios used.[31]

When we compare the international (country) 3FM with the country 3FM the differences are much less pronounced. First of all, the adjusted R^2s of the international model are marginally higher. This means that the foreign factors hardly have any extra explanatory power compared to the domestic factors, which is in line with expectation, since these factors are highly correlated. However, the international version of the 3FM is not necessarily better in explaining the portfolio returns. In all cases for BE/ME-sorted portfolios the country model has a better performance measured by the mean absolute pricing error. This result is somewhat striking at first glance, but is also reported by Griffin (2002). He finds the same result using data for the UK, US, Japan and Canada. Apparently, the local factors are far more informative in terms of asset pricing than the other factors are. As a robustness check, we also averaged the results for the bigger countries only (rows 4-6). In that case, all conclusions are the same, except for the 3-sort, where the international country 3FM has a lower mean absolute pricing error than the country 3FM. Also, the difference between the domestic and the euro area 3FM is less pronounced, but the domestic 3FM is clearly favorable on both performance measures.

Table 3.5 shows the results for size-sorted portfolios and the same asset pricing models. Again we see that euro area 3FM has the worst performance of three models by far. The R^2s almost double and the mean absolute pricing errors lower substantially ranging from 30% to 60% of the absolute pricing error of the euro area 3FM. The performance of the international and the country model are again very similar. The R^2s of the international 3FM are slightly higher than those of the country 3FM, while the results based on the absolute pricing errors differ over the different number of portfolios used. Either way, it can be concluded that the three added factors in the international model do not add much explanatory power.

3.4.2 The industry vs. the euro area 3FM

Several studies (amongst others, Fama and French, 1997; Van Vliet and Post, 2004) show that pricing industry(-sorted) portfolios is very difficult. Most of the studies, however, use global factors in the asset-pricing models. We propose to use a different specification of the Fama-French 3FM: a factor-model using industrial factors. We test the performance of a pure industry 3FM against a euro-area 3FM, as given by equations (3.2) and (3.7). For

[31] In case we only use three portfolios, we know that the portfolios contain enough stocks, but on the other hand this favors the country model. After all, the domestic market is split into three smaller subsets and hence the explanatory variables in the country three-factor model are more correlated with the dependent variables. Therefore, we should also consider a higher number of portfolios (in our case we used 6 and 10 portfolios). The drawback of using more different portfolios is that the number of stocks per portfolio is decreasing. This holds especially for smaller countries, like Greece and Ireland that have less than 20 stocks in the beginning of the sample. For this reason we also check all our results in case we only consider the bigger countries (or in the following section industries), which contains at least 50 stocks throughout the whole sample.

Table 3.5

Country vs. euro area model, size sorted portfolios, full sample

This table presents the two performance measures resulting from regressing the size sorted portfolios of the countries considered using the full sample on three different asset pricing models: the euro area 3FM, the international country 3FM and the country 3FM (see equation (3.2), (3.4) and (3.5) respectively). For each model the mean absolute pricing error is stated in the first column of the model and the second column contains the average adjusted R^2. The top rows depict the averages of the performance measures for all countries and the three following rows average over the four largest countries (France, Germany, Italy and the Netherlands).

The number of portfolios and Country considered	European model		International model		Country model	
	Av. $\|\alpha\|$	Av. R^2	Av. $\|\alpha\|$	Av. R^2	Av. $\|\alpha\|$	Av. R^2
Average, 3	0.349	0.495	0.139	0.871	0.153	0.864
Average, 6	0.398	0.435	0.236	0.765	0.240	0.757
Average, 10	0.467	0.383	0.329	0.670	0.319	0.661
(only big countr.) 3	0.202	0.676	0.100	0.917	0.087	0.913
(only big countr.) 6	0.238	0.617	0.180	0.831	0.173	0.826
(only big countr.) 10	0.324	0.559	0.265	0.755	0.259	0.747
Germany 3	0.056	0.718	0.081	0.909	0.075	0.908
Germany 6	0.167	0.640	0.144	0.832	0.115	0.830
Germany 10	0.261	0.573	0.184	0.739	0.168	0.738
Belgium 3	0.131	0.542	0.042	0.817	0.054	0.807
Belgium 6	0.197	0.449	0.097	0.701	0.162	0.691
Belgium 10	0.243	0.383	0.158	0.597	0.212	0.585
Spain 3	0.144	0.582	0.156	0.905	0.140	0.904
Spain 6	0.241	0.527	0.195	0.840	0.188	0.839
Spain 10	0.281	0.479	0.356	0.770	0.320	0.769
Finland 3	0.947	0.409	0.192	0.850	0.164	0.826
Finland 6	0.720	0.364	0.387	0.747	0.187	0.711
Finland 10	0.699	0.303	0.446	0.649	0.308	0.619
France 3	0.189	0.734	0.026	0.900	0.034	0.892
France 6	0.330	0.676	0.245	0.804	0.278	0.793
France 10	0.437	0.598	0.449	0.712	0.502	0.696
Greece 3	0.649	0.167	0.257	0.896	0.330	0.895
Greece 6	0.742	0.148	0.328	0.794	0.346	0.795
Greece 10	0.802	0.138	0.386	0.698	0.431	0.696
Ireland 3	0.274	0.344	0.093	0.813	0.239	0.792
Ireland 6	0.429	0.261	0.244	0.630	0.421	0.606
Ireland 10	0.663	0.185	0.469	0.466	0.587	0.454
Italy 3	0.430	0.545	0.182	0.958	0.145	0.958
Italy 6	0.356	0.539	0.210	0.914	0.204	0.913
Italy 10	0.410	0.512	0.238	0.872	0.179	0.871
Netherlands 3	0.131	0.708	0.112	0.901	0.093	0.894
Netherlands 6	0.097	0.611	0.123	0.775	0.094	0.769
Netherlands 10	0.186	0.555	0.191	0.695	0.188	0.682
Austria 3	0.573	0.306	0.096	0.846	0.127	0.844
Austria 6	0.666	0.259	0.216	0.724	0.254	0.725
Austria 10	0.581	0.213	0.246	0.587	0.249	0.585
Portugal 3	0.309	0.386	0.291	0.783	0.281	0.781
Portugal 6	0.436	0.307	0.402	0.657	0.389	0.658
Portugal 10	0.574	0.276	0.491	0.590	0.370	0.579

Table 3.6

Industry vs. euro area model, book-to-market sorted portfolios, full sample

This table presents the two performance measures resulting from regressing the book-to-market sorted portfolios of the industries considered using the full sample on three different asset pricing models: the euro area 3FM, the international (industry) 3FM and the industry 3FM (see equation (3.2), (3.6) and (3.7) respectively). For each model the mean absolute pricing error is stated in the first column of the model and the second column contains the average adjusted R^2. The top rows depict the averages of the performance measures for all industries and the three following rows average over the six largest industries. (Basic Industries, General Industries, Cyclical Consumer Goods, Non-Cyclical Consumer Goods, Cyclical Services and Financials).

The number of portfolios and Industry considered	European model		International model		Industry model	
	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2
Average, 3	0.380	0.576	0.237	0.843	0.225	0.833
Average, 6	0.421	0.490	0.295	0.688	0.275	0.674
Average, 10	0.445	0.422	0.317	0.581	0.311	0.568
(only big industr.) 3	0.287	0.652	0.203	0.865	0.201	0.852
(only big industr.) 6	0.320	0.569	0.254	0.732	0.251	0.717
(only big industr.) 10	0.346	0.506	0.287	0.640	0.275	0.626
Resor 3	0.465	0.338	0.236	0.691	0.254	0.680
Resor 6	0.443	0.275	0.327	0.487	0.289	0.475
Resor 10	0.497	0.222	0.339	0.390	0.348	0.375
Basic 3	0.189	0.628	0.229	0.853	0.214	0.835
Basic 6	0.193	0.576	0.212	0.699	0.278	0.676
Basic 10	0.221	0.511	0.202	0.609	0.255	0.582
Genin 3	0.361	0.741	0.375	0.862	0.421	0.851
Genin 6	0.612	0.632	0.446	0.733	0.383	0.719
Genin 10	0.553	0.576	0.381	0.665	0.325	0.651
Cycgd 3	0.252	0.618	0.166	0.859	0.155	0.852
Cycgd 6	0.123	0.518	0.220	0.704	0.281	0.698
Cycgd 10	0.300	0.460	0.352	0.608	0.387	0.600
Ncycg 3	0.459	0.498	0.095	0.833	0.093	0.814
Ncycg 6	0.448	0.422	0.128	0.674	0.123	0.657
Ncycg 10	0.459	0.347	0.258	0.557	0.256	0.548
Cyser 3	0.208	0.667	0.088	0.846	0.099	0.828
Cyser 6	0.285	0.554	0.241	0.704	0.199	0.678
Cyser 10	0.329	0.489	0.281	0.595	0.214	0.576
Ncysr 3	0.487	0.536	0.233	0.867	0.295	0.857
Ncysr 6	0.434	0.456	0.214	0.722	0.274	0.701
Ncysr 10	0.466	0.358	0.283	0.585	0.333	0.571
Utils 3	0.114	0.424	0.063	0.866	0.060	0.868
Utils 6	0.194	0.312	0.179	0.644	0.132	0.639
Utils 10	0.361	0.236	0.260	0.481	0.244	0.471
Totlf 3	0.253	0.760	0.264	0.934	0.222	0.934
Totlf 6	0.262	0.713	0.278	0.878	0.244	0.877
Totlf 10	0.214	0.654	0.246	0.806	0.214	0.801
Itech 3	1.009	0.550	0.616	0.814	0.440	0.809
Itech 6	1.216	0.445	0.708	0.631	0.552	0.624
Itech 10	1.050	0.364	0.566	0.519	0.531	0.509

Table 3.7
Industry vs. euro area model, size-sorted portfolios, full sample

This table presents the two performance measures resulting from regressing the size-sorted portfolios of the industries considered using the full sample on three different asset pricing models: the euro area 3FM, the international (industry) 3FM and the industry 3FM (see equation (3.2), (3.6) and (3.7) respectively). For each model the mean absolute pricing error is stated in the first column of the model and the second column contains the average adjusted R^2. The top rows depict the averages of the performance measures for all industries and the three following rows average over the six largest industries. (Basic Industries, General Industries, Cyclical Consumer Goods, Non-Cyclical Consumer Goods, Cyclical Services and Financials).

The number of portfolios and Industry considered	European model		International model		Industry model	
	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2
Average, 3	0.359	0.624	0.182	0.838	0.173	0.822
Average, 6	0.376	0.540	0.224	0.720	0.218	0.700
Average, 10	0.465	0.464	0.337	0.612	0.320	0.593
(only big industr.) 3	0.259	0.704	0.126	0.877	0.113	0.858
(only big industr.) 6	0.306	0.630	0.187	0.775	0.173	0.752
(only big industr.) 10	0.349	0.556	0.239	0.673	0.222	0.650
Resor 3	0.273	0.445	0.114	0.710	0.098	0.686
Resor 6	0.233	0.336	0.159	0.542	0.129	0.517
Resor 10	0.493	0.253	0.359	0.433	0.373	0.422
Basic 3	0.190	0.717	0.135	0.880	0.123	0.861
Basic 6	0.321	0.658	0.241	0.783	0.189	0.757
Basic 10	0.354	0.583	0.316	0.683	0.244	0.654
Genin 3	0.344	0.788	0.189	0.894	0.081	0.842
Genin 6	0.537	0.652	0.350	0.778	0.214	0.726
Genin 10	0.654	0.600	0.363	0.701	0.322	0.650
Cycgd 3	0.209	0.698	0.108	0.873	0.113	0.863
Cycgd 6	0.159	0.603	0.103	0.750	0.169	0.738
Cycgd 10	0.207	0.520	0.173	0.644	0.187	0.633
Ncycg 3	0.253	0.587	0.093	0.831	0.101	0.814
Ncycg 6	0.228	0.514	0.162	0.703	0.186	0.685
Ncycg 10	0.210	0.444	0.157	0.597	0.159	0.582
Cyser 3	0.371	0.679	0.111	0.869	0.115	0.859
Cyser 6	0.335	0.635	0.115	0.775	0.132	0.753
Cyser 10	0.349	0.560	0.179	0.663	0.184	0.634
Ncysr 3	0.423	0.565	0.369	0.806	0.399	0.795
Ncysr 6	0.475	0.457	0.420	0.669	0.480	0.657
Ncysr 10	0.593	0.373	0.611	0.554	0.599	0.540
Utils 3	0.351	0.411	0.131	0.784	0.161	0.782
Utils 6	0.403	0.330	0.184	0.642	0.176	0.638
Utils 10	0.397	0.261	0.212	0.510	0.266	0.505
Totlf 3	0.187	0.752	0.121	0.915	0.142	0.911
Totlf 6	0.255	0.718	0.149	0.859	0.151	0.850
Totlf 10	0.321	0.630	0.244	0.753	0.239	0.747
Itech 3	0.985	0.599	0.451	0.822	0.396	0.813
Itech 6	0.816	0.502	0.361	0.696	0.359	0.680
Itech 10	1.075	0.419	0.760	0.579	0.632	0.566

reasons of comparison we also include an international industry 3FM (similar to the international country 3FM) as denoted by equation (3.6). The test assets for these models are formed by sorting all assets of a specific industry on book-to-market or on size. Thus, we use BE/ME-sorted industry portfolios and size-sorted industry portfolios in this section.

The results presented in Table 3.6 coincide with the results of the previous subsection. The euro area 3FM does not contain enough information to price the BE/ME-sorted portfolios as efficient as the international and the industry 3FM, that both contain the local industry factors. The R^2s of the euro area 3FM are significantly lower and mean absolute pricing error is higher. The difference between the international industry and (local) industry 3FM is very small. The industry model does have lower absolute pricing error for all number of book-to-market sorted portfolios (3, 6 and 10), but this only holds on average and not for each industry separately. The results on the size-sorted portfolios contain no surprises (see Table 3.7). The conclusions are the same as for the book-to-market sorted sector portfolios stating that the more local 3FM is better capable in explaining the cross-section of stock returns. In order to test whether our results are not driven by outliers in smaller industries, we also present the performance measures for the bigger sectors only. These are reported on rows 4-6 of Table 3.6 and 3.7. The performance for all models improves slightly, which might be explained by the fact that the test portfolios contain more stocks than the industry portfolios of smaller sectors. The relative performance, however, remains the same. Summarizing, Tables 3.6 and 3.7 show that a local industry 3FM is more capable of explaining the cross-section of industry returns than a euro area version of this model. This result shows that an industry-based 3FM might be more appropriate in terms of pricing industry portfolios. Clearly, more research needs to be done in this area, but we leave this for future research.

The sections 3.4.1 and 3.4.2 have shown that a local three-factor model is preferred over the euro area version of the model over the whole sample. Using BE/ME- and size-sorted portfolios we have shown that a domestic 3FM or an industry 3FM has a clear outperformance compared to the euro area 3FM in terms of both R^2s and the mean absolute pricing error. In the following section we will present the results in case the methodology is applied to sub periods of our sample in order to test the behavior of these models over time.

3.4.3 European integration and the relative performance of asset pricing models

The European Monetary Union has been a very dynamic environment during our sample period. A number of changes in the monetary and legislation system have been implemented in order to achieve a higher level of (real) integration. For example, institutional investors were restricted concerning investments in foreign stocks (stocks denoted in different currency). This restriction is relaxed with respect to other euro-participating countries and since the advent of the euro this restriction was relaxed in a

Table 3.8
Country vs. euro area model, results for the sub samples

This table presents the two performance measures resulting from regressing the book-to-market sorted and size-sorted portfolios of the industries considered for two different sub samples on three different asset pricing models: the euro area 3FM, the international (industry) 3FM and the industry 3FM (see equation (3.2), (3.6) and (3.7) respectively). For each model the mean absolute pricing error is stated in the first column of the model and the second column contains the average adjusted R^2. The first three rows of each panel depict the averages of the performance measures for all countries and the three following rows average over the four largest countries (France, Germany, Italy and the Netherlands). Panel A and B present the figures for both sub samples for the book-to-market sorted portfolios. Panel C and D present the same statistics for the size-sorted portfolios.

The number of portfolios and industries considered	European model		International model		Industry model	
	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2
PANEL A: FIRST SUBSAMPLE 1991:07 – 1997:01, BOOK-TO-MARKET SORTED PORTFOLIOS						
Average, 3	0.439	0.458	0.181	0.894	0.175	0.889
Average, 6	0.501	0.409	0.303	0.783	0.292	0.776
Average, 10	0.590	0.353	0.417	0.667	0.399	0.656
(only big countr.) 3	0.364	0.599	0.173	0.920	0.140	0.914
(only big countr.) 6	0.359	0.549	0.238	0.839	0.204	0.832
(only big countr.) 10	0.388	0.495	0.284	0.757	0.244	0.743
PANEL B: SECOND SUBSAMPLE 1997:02 – 2002:08, BOOK-TO-MARKET SORTED PORTFOLIOS						
Average, 3	0.653	0.515	0.348	0.851	0.332	0.847
Average, 6	0.613	0.454	0.423	0.725	0.411	0.717
Average, 10	0.675	0.401	0.538	0.627	0.499	0.616
(only big countr.) 3	0.438	0.705	0.298	0.878	0.324	0.871
(only big countr.) 6	0.464	0.636	0.465	0.769	0.422	0.760
(only big countr.) 10	0.469	0.580	0.467	0.695	0.439	0.685
PANEL C: FIRST SUBSAMPLE 1991:07 – 1997:01, SIZE-SORTED PORTFOLIOS						
Average, 3	0.492	0.482	0.175	0.891	0.178	0.886
Average, 6	0.539	0.424	0.273	0.797	0.272	0.791
Average, 10	0.571	0.366	0.357	0.691	0.352	0.688
(only big countr.) 3	0.350	0.621	0.107	0.928	0.094	0.924
(only big countr.) 6	0.374	0.567	0.165	0.849	0.131	0.846
(only big countr.) 10	0.388	0.514	0.229	0.776	0.224	0.772
PANEL D: SECOND SUBSAMPLE 1997:02 – 2002:08, SIZE-SORTED PORTFOLIOS						
Average, 3	0.520	0.529	0.238	0.864	0.197	0.854
Average, 6	0.547	0.467	0.316	0.759	0.313	0.748
Average, 10	0.714	0.421	0.495	0.669	0.450	0.655
(only big countr.) 3	0.248	0.732	0.212	0.920	0.177	0.915
(only big countr.) 6	0.360	0.674	0.321	0.837	0.312	0.829
(only big countr.) 10	0.496	0.620	0.483	0.766	0.460	0.753

Table 3.9
Industry vs. euro area model, results for the sub samples

This table presents the two performance measures resulting from regressing the book-to-market sorted and size-sorted portfolios of the industries considered for two different sub samples on three different asset pricing models: the euro area 3FM, the international (industry) 3FM and the industry 3FM (see equation 2, 6 and 7 respectively). For each model the mean absolute pricing error is stated in the first column of the model and the second column contains the average adjusted R2. The first three rows of each panel depict the averages of the performance measures for all industries and the three following rows average over the six largest industries. (Basic Industries, General Industries, Cyclical Consumer Goods, Non-Cyclical Consumer Goods, Cyclical Services and Financials). Panel A and B present the figures for both sub samples for the book-to-market sorted portfolios. Panel C and D present the same statistics for the size-sorted portfolios.

The number of portfolios and industries considered	European model		International model		Industry model	
	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2	Av. $\lvert\alpha\rvert$	Av. R^2
PANEL A: FIRST SUBSAMPLE 1991:07 – 1997:01, BOOK-TO-MARKET SORTED PORTFOLIOS						
Average, 3	0.433	0.634	0.262	0.837	0.234	0.820
Average, 6	0.493	0.528	0.337	0.680	0.292	0.665
Average, 10	0.556	0.444	0.447	0.571	0.415	0.555
(only big industr.) 3	0.323	0.717	0.197	0.889	0.148	0.882
(only big industr.) 6	0.397	0.619	0.259	0.754	0.209	0.743
(only big industr.) 10	0.445	0.545	0.356	0.658	0.309	0.646
PANEL B: SECOND SUBSAMPLE 1997:02 – 2002:08, BOOK-TO-MARKET SORTED PORTFOLIOS						
Average, 3	0.407	0.560	0.312	0.850	0.344	0.844
Average, 6	0.578	0.482	0.483	0.696	0.483	0.686
Average, 10	0.530	0.420	0.434	0.600	0.457	0.591
(only big industr.) 3	0.341	0.633	0.263	0.868	0.313	0.857
(only big industr.) 6	0.472	0.557	0.409	0.741	0.422	0.729
(only big industr.) 10	0.443	0.502	0.386	0.655	0.422	0.643
PANEL C: FIRST SUBSAMPLE 1991:07 – 1997:01, SIZE-SORTED PORTFOLIOS						
Average, 3	0.374	0.669	0.264	0.843	0.243	0.825
Average, 6	0.413	0.577	0.335	0.726	0.314	0.706
Average, 10	0.561	0.485	0.530	0.604	0.486	0.582
(only big industr.) 3	0.267	0.762	0.192	0.888	0.170	0.878
(only big industr.) 6	0.324	0.672	0.237	0.786	0.229	0.774
(only big industr.) 10	0.393	0.588	0.330	0.679	0.299	0.662
PANEL D: SECOND SUBSAMPLE 1997:02 – 2002:08, SIZE-SORTED PORTFOLIOS						
Average, 3	0.409	0.613	0.155	0.840	0.209	0.826
Average, 6	0.499	0.536	0.279	0.725	0.335	0.707
Average, 10	0.556	0.467	0.395	0.630	0.430	0.617
(only big industr.) 3	0.328	0.687	0.108	0.883	0.166	0.867
(only big industr.) 6	0.445	0.626	0.252	0.784	0.293	0.763
(only big industr.) 10	0.487	0.556	0.333	0.691	0.357	0.673

more natural way. Clearly, this might have a considerable impact on financial markets. For example, if financial integration has increased during our sample period, we would expect that the (relative) performance of the euro area 3FM would increase compared to the country/industry (and international) 3FM. Therefore, we want to split our sample in two halves to test for differences over the two sub periods. Table 3.8 contains the results of the country, international and euro area 3FM model for both sub samples, for the book-to-market sorted test portfolios and for size-sorted portfolios.[32] Table 3.9 presents the same results of the industry portfolios using the industry, international industry and euro area 3FM.

Due to different market conditions the actual level of the performance measures are not directly comparable, but the conclusions to be drawn on the relative performance of the models are similar. In almost all cases, the euro area factor model is not able to perform better than any of the other models in both of the sample periods. Also, the performances of the international and local (both the (local) country and the (local) industry model) are not very much apart. More interesting, however, is to compare the relative performances over the different periods with each other. Let's define $\kappa_{i,j}$ as the ratio of the mean absolute pricing error of the model *i* over the corresponding value of the model *j*:

$$\kappa_{i,j} = \frac{\frac{1}{n}\sum_p |\alpha_{p,i}|}{\frac{1}{n}\sum_p |\alpha_{p,j}|} \tag{3.8}$$

Since a lower value of the alpha corresponds with a better performance of the model, a value of $\kappa_{country,euro\ area}$ that is lower than one, means that the country factor model performs better than the euro area factor model in terms of absolute pricing errors. This κ-indicator summarizes the relative performance of the two models into one number. In the rest of the analysis, we will only use the κ-indicator with the alphas of the euro area 3FM in the denominator. Then, in case the level of equity market integration between different countries (industries) has increased during our sample period, the κ-indicator shows a higher value for the second sub sample compared to the first sub sample.

Figure 3.1 shows the values of the κ-indicator for the different models and each sub sample.[33] The first two pairs of bars relate the mean absolute pricing error of the

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[32] Table 3.8 and 3.9 only report the average result for sake of brevity. The results for the individual countries are available from the author upon request.

[33] In order to calculate the values for κ we used the average value of the absolute alphas of the ten sorted portfolios. If the number of portfolios is small, we might favor the domestic (country or industry) model over the European model, because of a high correlation between the local market return and the local portfolios. The drawback of using more portfolios is that the number of assets per portfolio decreases. This is especially an issue

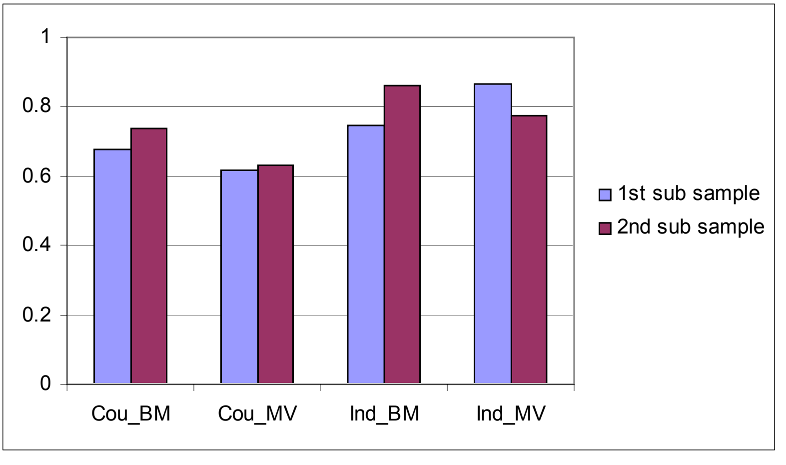
Figure 3.1

The values for κ averaged over all countries or industries

This figure shows the values for κ (as defined in equation 3.8) for all tested portfolios. κ is the ratio of average absolute alpha of the country or the industry 3FM over the corresponding value of the euro area 3FM.

$$\kappa_{i,EUR} = \frac{\frac{1}{n}\sum_p |\alpha_{p,i}|}{\frac{1}{n}\sum_p |\alpha_{p,EUR}|}$$

The first two couples of bars indicate the $\kappa_{country,euro\text{-}area}$ for the book-to-market sorted portfolios and the size-sorted portfolios. The third and fourth pair depict $\kappa_{country,euro\text{-}area}$ for these portfolios. The left bar of each pair represents the κ-indicator in the first sub sample and the right bar for the second sub sample. We used the pricing errors of 10-sorts in each case, but using a 3-sort or 6-sort gives similar conclusions. The ratios can easily be calculated using the numbers from the Tables 3.8 and 3.9 for the countries and industries respectively. For example, the most left bar uses the performance measures from Table 3.8, panel A, of the ten book-to-market portfolios (3rd row containing numbers): $\kappa = 0.399/0.590 = 0.68$.



country 3FM with the euro area 3FM. We see a slight increase in the relative performance of the euro-area 3FM for the book-to-market sorted portfolios, while for the size-sorted portfolios κ hardly changes over the different sub samples. The results for the comparison of the industry 3FM with the euro area 3FM are depicted in the two other pairs of bars.

when we study smaller countries like Greece and Ireland (see Table 2). Therefore, we will also examine the results for the bigger countries (industries) only.

These show mixed evidence with respect to the κ-indicator. The value of κ for the book-to-market sorted portfolios increases, while it decreases for the size-sorted industry portfolios. One could conclude that there are no significant changes in the relative performance of the different factor models over the sub samples. We should, however, bear in mind that these results are based on the whole sample and thus includes the smaller countries and industries. As mentioned before, this can influence our results. First of all, the portfolios of these countries are very small and we should be careful in interpreting their results. Secondly, although these countries have adopted the euro, they might still be less integrated with the European Monetary Union than other, bigger countries.

For that reason Figure 3.2 also depicts the κ-indicators in case only the bigger countries and bigger industries are considered.[34] Concentrating on the results for the industry sorted portfolios we are again confronted with mixed results. The value of κ for the size-sorted portfolios shows no change at all, while the κ-ratio for the book-to-market sorted industry portfolios gives a clear increase. The ratio is still below 1, which means that on average the local industry 3FM is better in terms of mean absolute pricing error than the euro area version of the model, but the difference is almost negligible. When we compare the country 3FM with its euro area counterpart, however, a clear difference between the first and second sub sample can be found. Where the euro area 3FM clearly performs worse in the first part of the sample (with κ-values of 63% for the book-to-market portfolios and 58% for the size-sorted portfolios), the performance of the two models is almost similar in the second part of the sample (the values of κ increased to 94% and 93% respectively). This result could likely be a consequence of the increased rate of integration in the EMU and it might indicate that asset pricing in the euro area has been changing.

A more detailed view on the performance measures for the four bigger countries shows that the conclusion is fairly robust. All four countries considered show an increase both for the book-to-market and the size-sorted portfolios, except for Germany in case book-to-market portfolios are studied (the κ-ratio decreased from 87% to 79% in that case). The overall result is robust. The number of portfolios used in the regressions (3 or 6 instead of 10) does not influence the outcome of our conclusions. Furthermore, one can argue that the euro area factors are still based on all countries, while factors based on the biggest four countries might show a different behavior. Unreported results show that the conclusions are similar when the "global" factors are based on the big countries only.[35]

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[34] A country or industry is considered big as soon as the number of assets in this group is higher than 50 for the complete sample. This means that only four countries are considered big in this sample: France, Germany, Italy and the Netherlands. There are six industries that meet this criterion: Basic Industries, General Industries, Cyclical Consumer Goods, Non-Cyclical Consumer Goods, Cyclical Services and Financials.

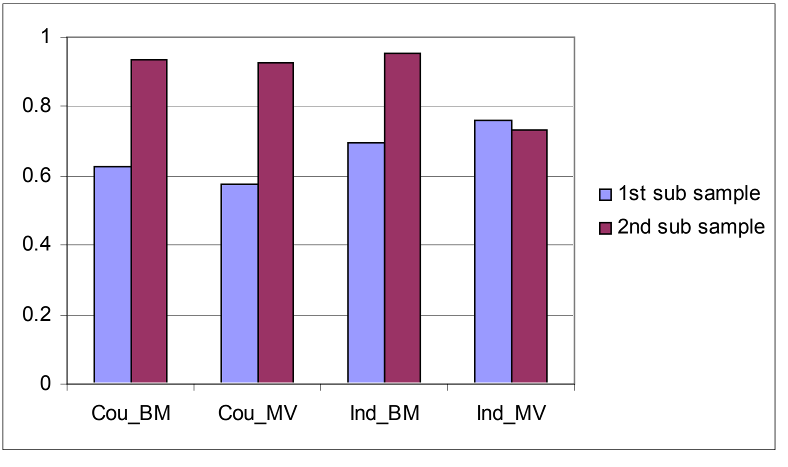
[35] These results are available upon request.

Figure 3.2
The values for κ averaged over all bigger countries (4) or industries (6)

This figure shows the values for κ (as defined in equation 3.8) for all tested portfolios. κ is the ratio of average absolute alpha of the country or the industry 3FM over the corresponding value of the euro area 3FM.

$$\kappa_{i,EUR} = \frac{\frac{1}{n}\sum_{p} |\alpha_{p,i}|}{\frac{1}{n}\sum_{p} |\alpha_{p,EUR}|}$$

The first two couples of bars indicate the $\kappa_{country,euro\text{-}area}$ for the book-to-market sorted portfolios and the size-sorted portfolios based on the bigger countries only (France, Germany, Italy and the Netherlands). The third and fourth pair depict $\kappa_{country,euro\text{-}area}$ for these portfolios base on the bigger industries (Basic Industries, General Industries, Cyclical Consumer Goods, Non-Cyclical Consumer Goods, Cyclical Services and Financials). The left bar of each pair represents the κ-indicator in the first sub sample and the right bar for the second sub sample. We used the pricing errors of 10-sorts in each case, but using a 3-sort or 6-sort gives similar conclusions. The ratios can easily be calculated using the numbers from the Tables 3.8 and 3.9 for the countries and industries respectively using the values based on the bigger groups only. For example, the most left bar uses the performance measures from Table 3.8, panel A, of the ten book-to-market portfolios based on the biggest countries (6th row containing numbers): $\kappa = 0.244/0.388 = 0.63$.



Concluding we can state the (local) country model is losing field against the European three-factor, although its performance is still slightly better. The industry asset-pricing model, however, outperforms the European version in both sub samples. A tentative conclusion would therefore be that industry factors are nowadays more important in terms of asset pricing than country factors concerning assets from the euro area. Though, we should bear in mind that the European models are not fully comparable given our choice of the methodology. In order to test this conclusion more research attention should be paid to the industry three-factor model.

3.5 Conclusions

In this chapter we examine different asset-pricing models applied to stocks in the euro area. All models are an interpretation of the Fama and French three-factor model, which contains a market factor, a small-minus-big factor and a high-minus-low factor (see equation 3.1)). Although Fama and French (1998) provide evidence for the international version of the model (i.e. when the factors are global), many practitioners and academics use a domestic version of this asset-pricing model. Moreover, Griffin (2002) shows that the domestic three-factor model clearly outperforms the global model for the US, Canada, Japan and the UK. In this chapter we study different domestic versions of the Fama and French three-factor model for the euro area. Motivated by the number of regulatory changes in the European Monetary Union, our sample period runs from 1991-2002. This period not only covers the introduction of the common currency, but also numerous harmonizing impulses in order to facilitate real and financial integration in the European Union.

The first part of this chapter centers on the euro area 3FM versus a country version for eleven euro-participating countries using both book-to-market and size-sorted portfolios. We show that the euro area 3FM clearly underperforms the country 3FM, as measured by both the mean absolute pricing error and the R^2. The international version of the model (which splits all factors into a domestic and a foreign part) has a similar performance as the country model. In other words, the three foreign factors hardly explain and sometimes even jeopardize the performance of the asset-pricing model.

We also test different asset pricing models for industry portfolios. In general, industry portfolios are very hard to price, as reported by Fama and French (1997) and Van Vliet and Post (2004). The models tested include again the euro area 3FM and a local industry asset-pricing model. The latter one contains three Fama-French factors that are fully based on stocks of one industry only. We examine the performance of these versions of the 3FM with BE/ME-sorted and size-sorted industry portfolios. The results indicate, similar to the comparison of the country 3FM with the euro area 3FM, that the industry 3FM (the "local" version of the model) outperforms the euro area 3FM. Although this finding is very surprising, it might suggest that an industry three-factor model can more easily explain industry portfolio returns. However, more specific research on industry portfolios is needed in order to understand industry portfolio dynamics.

We executed the same analyses for two equal sub periods. This is a robustness check on the validity of our conclusions. However, one can interpret the outcomes of the analyses as a measure for the European equity market integration. It is well known that the number of regulatory changes has been huge during the ongoing integration process in the European Union. Next to the harmonization of monetary and policy changes, the relaxation of investment restrictions for European institutional investors has had an enormous impact on the integration process. As a result, the relative performance of the euro area 3FM might increase compared to the local country 3FM. We document this increase in the relative performance for all major euro-participating countries (Germany, France, Italy and the Netherlands). In the first part of the sample the mean absolute pricing error of the local (country) 3FM is on average 40% lower than the euro area factor model, whereas this difference decreased to less than 10% for the second sub period (see Figure 3.2). This finding suggests that asset pricing in the European Monetary Union is changing as well. For the industry portfolios we find mixed evidence with respect to the relative performance of the different asset pricing models for the book-to-market and size-sorted portfolios. We do find, however, that the industry 3FM outperforms the euro area 3FM for all tested portfolios and periods. We realize that this is – to our knowledge- the first study applying the Fama-French methodology using industry based factors. Therefore, more research should be dedicated to the industry 3FM.

3.A Appendix

The methodology section explains the construction of all different three-factor models that are tested in this chapter. It is stated that the two European versions of the asset-pricing model are not comparable, which is explained in this appendix. The factors are defined as the weighted averages of the local country or local industry factors. For the market factor this does not constitute a difference. The European market factor is exactly the same, regardless whether it is constructed using the different country factors or the different industry factors:

$$
\begin{aligned}
EMRF_t &= w_{Dt-1} \cdot DMRF_t + w_{Ft-1} \cdot FMRF_t \\
&= w_{Dt-1} \cdot \sum_{i=1}^{S_D} w_{it-1}^{D} R_{it} + w_{Ft-1} \cdot \sum_{i=1}^{S_F} w_{it-1}^{F} R_{it} \\
&= \sum_{i=1}^{S_D} w_{it-1}^{EUR} R_{it} + \sum_{i=1}^{S_F} w_{it-1}^{EUR} R_{it} = \sum_{i=1}^{N} w_{it-1}^{EUR} R_{it} \\
&= \sum_{i=1}^{S_I} w_{it-1}^{EUR} R_{it} + \sum_{i=1}^{S_O} w_{it-1}^{EUR} R_{it} \\
&= w_{It-1} \cdot \sum_{i=1}^{S_I} w_{it-1}^{I} R_{it} + w_{Ot-1} \cdot \sum_{i=1}^{S_O} w_{it-1}^{O} R_{it} \\
&= w_{Ft-1} \cdot IMRF_t + w_{Ot-1} \cdot OMRF_t
\end{aligned}
\qquad \textbf{(3.9)}
$$

where w_{it-1}^{X} is the weight of asset *i* at time *t-1* measured by the market value of asset *i* relative to the total market value of country/industry *X* (which can be the domestic market *D*, the foreign market *F*, the European market *EUR*, the industry *I* or the other industries denoted by *O*) and S_X is the number of assets in country/industry *X* and *N* is the total number of assets.

The same does not hold for the SMB and HML portfolios. These portfolios are constructed as simple averages of smaller portfolios (SH, SM, SL and so on) and therefore the stocks will not have the same weights in case the portfolios are constructed using country or industry factor portfolios. Intuitively, this is also clear: the large stocks in a small country might not be a large stock in European context. However, we choose to follow the methodology of Griffin (2002) in order to be able to compare our results with the literature.

Another possibility is to construct the ESMB and EHML independently from the country and industry information. In that case the model would be a true European Fama and French three-factor model, but it would not be a nested model of the international country or international industry model anymore. This is a second reason to stick to the methodology of Griffin (2002). We also calculated the results using this other European model, but the results are not very different from the currently used model. In most cases the performance measures are approximately equal to each other.

Chapter 4

The World Price of Inflation Risk

4.1 Introduction

In a world in which neither investment nor consumption opportunity sets differ across countries, all risk-averse investors should hold their wealth in the risk-free asset and a single portfolio of risky assets that is common to all investors. This portfolio must be the market portfolio of risky assets. Grauer, Litzenberger, and Stehle (1976) develop an International Capital Asset Pricing Model (ICAPM) in which the global market portfolio is the only priced risk factor. When purchasing power parity (PPP) does not hold, investors in different countries have different consumption opportunity sets.[36] This implies that there is heterogeneity in their evaluation of the (real) returns from the same security. In that case, expected excess returns on risky factors are a linear function of their covariance with the global market portfolio as well as their covariance with nominal exchange rate risk factors.

[36] Deviations from PPP occur either because of differences in preferences across countries or due to deviations from the law of one price. We refer to Adler and Dumas (1983) for an exposition of this point.

International asset pricing models in the presence of deviations from PPP are developed by e.g. Solnik (1974), Sercu (1980), Stulz (1981), and Adler and Dumas (1983).[37]

While several panel studies of PPP (e.g. Taylor and Sarno (1998) and Wu and Wu (2001)) present evidence of mean reversion in real exchange rates in the long run, numerous empirical papers show that substantial deviations from PPP occur at short horizons.[38] This implies that asset prices may well be affected by both global market and currency risk factors. Dumas and Solnik (1995) report evidence in favor of foreign exchange risk premia in the conditional multifactor ICAPM framework of Solnik (1974) and Sercu (1980). They examine the stock market indices of Germany, Japan, the U.K., and the U.S. over the period 1970-1991. De Santis and Gérard (1998) employ a more comprehensive econometric methodology to test the ICAPM for the same four countries over the period 1973-1994. Their analysis supports a conditional ICAPM that includes both global market risk and three currency risk factors related to the German mark, the Japanese yen, and the British pound. In an unconditional analysis, Vassalou (2000) finds that exchange rate factors can explain part of the cross-sectional variation of the returns of individual securities within 10 industrialized countries over the period 1973-1990.

This chapter is focused on two potentially important restrictions in the ICAPM literature: (i) inflation rates are assumed to be constant in the theoretical model of Solnik (1974) and Sercu (1980) as well as in the empirical tests by Dumas and Solnik (1995) and De Santis and Gérard (1998) and (ii) in the model of Adler and Dumas (1983) the prices of inflation and nominal exchange rate risk are assumed to be equal. Relaxing these restrictions leads to a model in which asset returns depend on their sensitivity to both inflation risk and nominal exchange rate risk. There are three reasons why we think this is important. First, while inflation rates are known to be substantially less volatile than nominal exchange rates, to our knowledge no study exists that explicitly tests this restriction in the Solnik-Sercu model. Our study provides empirical evidence against the assumption that domestic inflation is non-stochastic. Second, outside the international asset pricing literature, many studies regard inflation risk as an important source of systematic risk. Recent theoretical term structure models by e.g. Buraschi and Jiltsov (2003) and Ang and Bekaert (2004) explicitly take account of priced inflation risk. Evans (1998) strongly supports the presence of time-varying inflation risk premia in U.K. index-linked bonds. While this does not imply that investors should hold hedge portfolios that provide a hedge against fluctuations in inflation differentials, disregarding inflation risk could have an important impact in the framework of an ICAPM. However, we are not aware of any international asset-pricing model that incorporates this potentially important risk factor.

[37] See Dumas (1994) and Stulz (1995) for an overview of international asset pricing.
[38] Examples are Froot and Rogoff (1995), Chinn (2002), and Lopez and Papell (2003).

Third, an ICAPM without inflation risk factors neglects the possibility that *real* exchange rate risk is priced when nominal exchange rate fluctuations are absent. This may be relevant in the context of European currency risk. Nominal exchange rate fluctuations within the European Monetary Union (EMU) ceased to exist at the introduction of the euro in 1999. This does not necessarily imply, however, that European inflation risk is not priced in asset returns.[39]

We estimate and test the conditional version of our model including priced risk factors related to the global market portfolio, nominal exchange rates, and inflation differentials. We study the equity markets of France, Germany, Japan, the U.K., and the U.S. over the period 1975:01-1998:12. Following De Santis and Gérard (1998), we employ a parsimonious multivariate GARCH process to test the pricing implications of the model. Our findings strongly support a model that includes inflation risk in addition to global market and nominal exchange rate risk. We confirm the result of De Santis and Gérard (1998) and De Santis, Gérard, and Hillion (2003) that the (time-varying) prices of nominal exchange rate risk are significantly different from zero. In addition, we also find strong evidence in favor of priced inflation risk for all countries in the sample. The hypothesis that the world prices of inflation risk are constant over time and the hypothesis that they are equal to zero are rejected at any conventional statistical significance level. We show that inflation risk is not only statistically significant, but also has an economically important contribution to expected returns on international securities. Inflation risk premia in asset returns are generally of the same order of magnitude as nominal exchange rate risk premia. Our results can be interpreted as evidence against the restrictions imposed by the ICAPM

An interesting and relevant application of our model concerns the post-euro period. While nominal exchange rate fluctuations have terminated within the euro area in 1999, differences in inflation may entail nontrivial real exchange rate risk. Recent work by Koedijk, Tims, and van Dijk (2004) presents evidence against the hypothesis of PPP for individual country pairs within the euro area. In a conditional test of the model including inflation risk over the period 1975-2003, we find that the time-varying price of inflation risk related to the German-French inflation differential is significant over the post-euro period. This evidence suggests that even for economically closely integrated countries

[39] Several empirical studies indicate that substantial real exchange rate changes (i.e. inflation differentials) occur within a single currency zone. Parsley and Wei (1996) report half-lifes of price discrepancies for 51 goods and services in 48 U.S. cities amounting to 1 to 4 years. Cecchetti, Mark, and Sonora (2002) consider consumer price indices for 19 U.S. cities over the period 1918-1995. They estimate the half-life of PPP deviations to be approximately 9 years. Differences in inflation rates measured over ten-year intervals can differ by as much as 1.6 percent per annum. Rogers (2001) constructs price indices for 26 European cities over the period 1990-1999 and concludes that "… deviations from the law of one price are large," although price dispersion across cities has been reduced over the past decade. Lutz (2002) analyzes four different data sets of final goods prices in European countries and finds limited evidence that price dispersion has decreased in the past decade.

investors demand a risk premium for their exposure to inflation risk. These results may have important implications in the context of portfolio management and capital budgeting decisions.

The chapter is organized as follows. In section 4.2 we review the literature on international asset pricing models and we discuss the ICAPM employed in our asset pricing tests. Section 4.3 provides a description of the methodology. Section 4.4 discusses the data and presents summary statistics. In section 4.5 we present the results of our empirical analysis of the modified ICAPM, while section 4.6 applies the framework of the ICAPM including inflation risk to the post-euro area. Section 4.7 concludes.

4.2 The model

Our study starts out with the ICAPM of Adler and Dumas (1983). The model can be constructed as follows. Consider a world economy with L + 1 countries (currencies), numbered l = 0, 1, …, L, with currency 0 as the measurement or numeraire currency.[40] Apart from the measurement currency deposit, there are $M = N + L + 1$ securities, comprising of N equities or portfolios of equities, L non-measurement currency deposits, and the world portfolio of equities which is the M^{th} and last security. All returns are measured in the numeraire currency and in excess of the risk-free rate, which corresponds to the short-term deposit rate in the numeraire currency. The pricing restrictions on asset i imposed by the conditional version of the ICAPM of Adler and Dumas (1983) can be expressed as follows:

$$E[r_{it} \mid \Omega_{t-1}] = \delta_{m,t-1}\,\text{cov}[r_{it}, r_{mt} \mid \Omega_{t-1}] + \sum_{l=0}^{L} \delta_{l,t-1}\,\text{cov}[r_{it}, \pi_{l0t} \mid \Omega_{t-1}] \qquad i = 1,\dots,M \quad \textbf{(4.1)}$$

where

$$\delta_{m,t-1} = \theta_{t-1} \equiv \frac{1}{\sum_{l=0}^{L} \frac{W_{l,t-1}}{W_{t-1}} \times \frac{1}{\theta_l}} \qquad \textit{and} \quad \delta_{l,t-1} = \theta_{t-1}\left(\frac{1}{\theta_l} - 1\right)\frac{W_{l,t-1}}{W_{t-1}}$$

[40] As is pointed out by e.g. Adler and Dumas (1983, footnote 3) and Stulz (1995, p. 219), the ICAPM is not specifically international in the sense that consumption opportunity sets can also differ within a country. "International" asset pricing models may therefore also apply to a single currency zone such as the U.S. Stulz (1995) contends that governments affect savings and lending decisions of investors by (i) defining the rights and obligations of the holders of financial assets issued within a country, (ii) defining the rights and obligations of the residents of a country (for instance in relation to taxation and the trading of assets), and (iii) defining legal tender within a country. This distinguishes "international" finance from "domestic" finance.

In equation (4.1) r_{it} denotes the nominal return on security or portfolio i from time $t-1$ to t in excess of the risk-free rate, Ω_{t-1} is the information set that investors use in choosing their portfolios, r_{mt} is the nominal return on the world market portfolio in excess of the risk-free rate, and π_{l0t} is the domestic inflation rate of country l measured in the numeraire currency. These domestic inflation rates can be decomposed as $\pi_{l0t} = s_{lt} + \pi_{lt}$, where s_{lt} denotes the nominal exchange rate change of currency l in terms of currency 0 and π_{lt} is the domestic inflation rate of country l measured in currency l from time $t-1$ to t. Furthermore, θ_l is the coefficient of relative risk aversion for investors from country l, θ_{t-1} is an average of the risk aversion coefficients of all countries, weighted by its relative wealth at time $t-1$ as represented by $W_{l,t-1}/W_{t-1}$. Dumas and Solnik (1995) refer to the time-varying coefficient $\delta_{m,t-1}$ in equation (4.1) as the "world price of market risk."[41] They call the time-varying coefficients $\delta_{l,t-1}$ the "world prices of exchange rate risk."

The ICAPM of Solnik (1974) and Sercu (1980) is a special case of equation (4.1). In the Solnik-Sercu model, the domestic inflation rates expressed in local currency π_{lt} (l = 0, 1, …, L) are assumed to be non-stochastic. Therefore, the $L+1$ covariance terms in equation (4.1) collapse into L covariance terms with the nominal exchange rates. The only two empirical studies we are aware of that empirically test the ICAPM, i.e. Dumas and Solnik (1995) and De Santis and Gérard (1998), also adopt the restriction that inflation rates are constant over time. No research has been done on the validity of this restriction. When we relax the assumption that inflation rates are non-stochastic and only assume that the domestic inflation rate in the numeraire country (expressed in the numeraire currency) is constant, we obtain an intuitively appealing representation of the ICAPM:[42]

$$E[r_{it} \mid \Omega_{t-1}] = \delta_{m,t-1}\operatorname{cov}[r_{it}, r_{mt} \mid \Omega_{t-1}] + \sum_{l=1}^{L} \delta_{l,t-1}\operatorname{cov}[r_{it}, q_{lt} \mid \Omega_{t-1}] \quad i = 1,\dots,M \qquad \textbf{(4.2)}$$

where $q_{lt} \equiv \pi_{l0t} - \pi_{0t} = s_{lt} + \pi_{lt} - \pi_{0t}$ is the real exchange rate change of currency l in terms of currency 0. Hence, this version of the ICAPM incorporates the world price of market risk and L "world prices of *real* exchange rate risk." This specification is consistent with investors maximizing their wealth in real terms and thus holding portfolios that provide a hedge against real (not nominal) exchange rate changes. The model in equation (4.2) is less restrictive than the Solnik-Sercu version of the ICAPM and allows for the possibility of priced real exchange rate risk when nominal exchange rates are fixed. Section 4.5 of this chapter provides an empirical test of the conditional version of this model.

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[41] Other authors, e.g. Harvey (1991), use the term "the world price of covariance risk" for $\delta_{m,t-1}$.

[42] Note that the number of risk premia in this model is reduced to L, as the domestic inflation rate in the numeraire country is assumed to be non-stochastic. Without loss of generality, we can subtract this inflation rate from the domestic inflation rates of the other L countries expressed in the numeraire currency.

The covariance between r_{it} and q_{lt} could possibly reflect two separate sources of risk: nominal exchange rate risk and inflation risk. An interesting and germane issue is the relative importance of these risk factors. A related question is whether they reinforce each other or partially cancel each other out. The distinction between these two separate sources of risk may become especially relevant when we study inflation risk in the euro area. Within the euro area, real exchange rate risk contains both the nominal exchange rate and inflation risk components before the introduction of the euro in 1999 and only the inflation risk component after 1999. If inflation risk is priced in international asset returns, this is also likely to constitute a relevant priced risk factor in the post-euro era. Therefore, we extend the model specified in equation (4.2) by allowing the prices of nominal exchange rate risk and inflation risk to differ:

$$E[r_{it} \mid \Omega_{t-1}] = \delta_{m,t-1} \operatorname{cov}[r_{it}, r_{mt} \mid \Omega_{t-1}] + \sum_{l=1}^{L} \varphi_{l,t-1} \operatorname{cov}[r_{it}, s_{lt} \mid \Omega_{t-1}] \\ + \sum_{l=1}^{L} \gamma_{l,t-1} \operatorname{cov}[r_{it}, (\pi_{lt} - \pi_{0t}) \mid \Omega_{t-1}] \qquad i = 1,\dots,M \tag{4.3}$$

We refer to the time-varying coefficients as the world prices of nominal exchange rate risk and to as the "world prices of inflation risk." Estimates and tests of this model are presented in section 4.5. A rejection of the hypothesis that $\varphi_{l,t-1}$ and $\gamma_{l,t-1}$ are equal can be interpreted as evidence against the ICAPM.

4.3 Empirical methodology

We want to estimate the conditional version of models (2) and (3). We employ the parsimonious multivariate generalized autoregressive conditionally heteroskedastic (GARCH) approach of De Santis and Gérard (1997, 1998).[43] Our starting point is the conditional ICAPM with real exchange rate risk factors as depicted in equation (4.2). This equation states the moment conditions for the excess returns of the assets under consideration. Adding a disturbance term orthogonal to the information available at the end of time $t-1$ yields the econometric representation of the model that can be used to estimate the risk premia:

$$r_t = \delta_{m,t-1} h_{m,t} + \sum_{l=1}^{L} \delta_{l,t-1} h_{n+l,t} + \varepsilon_t \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{4.4}$$

[43] This methodology has been widely adopted in the literature, see e.g. Carrieri (2001), Carrieri, Errunza, and Majerbi (2003), and De Santis, Gérard, and Hillion (2003).

where H_t is the $(M \times M)$ covariance matrix of the excess returns at time t and $h_{i,t}$ is the i^{th} column of the covariance matrix H_t. The world prices of market and real exchange rate risk are time-varying and are function of a number of instrumental variables Z_{t-1} that represent the information set Ω_{t-1}.

If all investors are risk averse, the world price of market risk is positive (see equation (4.1)). Following De Santis and Gérard (1997), we force the price of market risk to satisfy this restriction by modeling the risk premium as an exponential function of the information variables. The real exchange rate risk premia are not restricted to be positive and hence the prices of real exchange rate risk are modeled as a linear function of the information variables:

$$\delta_{m,t-1} = \exp(\kappa'_m \cdot Z_{t-1}) \tag{4.5}$$

$$\delta_{l,t-1} = \kappa'_l \cdot Z_{t-1} \qquad l = 1,\dots,L \tag{4.6}$$

The data section covers in detail which instrumental variables are used.

An important and well-documented characteristic of security returns is the heteroskedasticity in their volatilities. This feature has to be taken into account when estimating the world prices of risk. Therefore, we follow the approach of De Santis and Gérard (1997, 1998) by imposing a diagonal GARCH process on the conditional second moments of the assets. In other words, H_t depends only on past squared residuals and an autoregressive component, while the covariances depend on past cross products of residuals and an autoregressive component. Furthermore, we assume that the process is covariance stationary. The process for H_t can then be written as follows:

$$H_t = H_0 * (\iota\iota' - aa' - bb') + aa' * \varepsilon_{t-1}\varepsilon'_{t-1} + bb' * H_{t-1} \tag{4.7}$$

where H_0 is the unconditional variance-covariance matrix of the residuals, ι is a $(M \times 1)$ vector of ones, a and b are $(M \times 1)$ vectors containing the unknown parameters and * denotes the Hadamard product (element by element matrix multiplication). H_0 is not directly observable, but can be consistently estimated using the iterative procedure developed by De Santis and Gérard (1997). In the first iteration of this estimation procedure, H_0 is set equal to the sample covariance matrix of the returns. In subsequent steps, H_0 is updated using the estimated residuals at the end of the previous iteration. For a detailed discussion of the properties of the GARCH parameterization we refer to De Santis and Gérard (1997).

Under the assumption that the errors are conditionally normally distributed, we can express the log-likelihood function as follows:

$$\ln L(\Psi) = -\frac{TM}{2}\ln 2\pi - \frac{1}{2}\sum_{t=1}^{T}\ln|H_t(\Psi)| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t(\Psi)' H_t(\Psi)^{-1}\varepsilon_t(\Psi) \tag{4.8}$$

where Ψ is the vector of all unknown parameters. We use quasi-maximum likelihood (QML) standard errors obtained with the estimation methodology proposed by Bollerslev and Wooldridge (1992), because the restriction of conditional normality is often violated. The model parameterization described above is also employed for the model that incorporates nominal exchange rate and inflation risk factors separately (equation (4.3)). The econometric specification of this model can be expressed by:

$$r_t = \delta_{m,t-1} h_{m,t} + \sum_{l=1}^{L} \varphi_{l,t-1} h_{n+l,t} + \sum_{l=1}^{L} \gamma_{l,t-1} h_{n+L+l,t} + \eta_t \qquad \eta_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{4.9}$$

where the process for H_t is given in equation (4.7) and the risk premia are modeled as a function of the instrumental variables Z_{t-1} in the following way:

$$\delta_{m,t-1} = \exp(\kappa'_m \cdot Z_{t-1}) \tag{4.10}$$

$$\varphi_{l,t-1} = \lambda'_l \cdot Z_{t-1} \qquad l = 1,\ldots,L \tag{4.11}$$

$$\gamma_{l,t-1} = \mu'_l \cdot Z_{t-1} \qquad l = 1,\ldots,L \tag{4.12}$$

4.4 Data

We use monthly returns on stock indices for the G5 countries (France, Germany, Japan, the U.K., and the U.S.) in addition to a value-weighted world index over the period 1975:01-1998:12. For our analysis of the post-euro period we also consider data over the period 1999:01-2003:12. All stock index data are obtained from Morgan Stanley Capital International (MSCI) and include dividends. We collect nominal end-of-period exchange rates against the U.S. dollar from International Financial Statistics (IFS). Returns on both equity indices and exchange rates are discrete and expressed in terms of the German mark. We use consumer price index (CPI) data from IFS to compute real exchange rate returns and inflation rates. For the conditionally risk-free asset we take the return on the one-month euro-mark deposit quoted in London (extracted from Datastream). Monthly excess returns are computed by subtracting the risk-free rate from the monthly return on each security.

The choice of instrumental variables is potentially very important in conditional tests of asset pricing models. However, the model does not provide any guidance as to the choice of the information variables and the number of instrumental variables is limited by the econometric methodology. Our selection of instruments builds on previous empirical research (notably Harvey (1991), Ferson and Harvey (1993), Dumas and Solnik (1995) and De Santis and Gérard (1997, 1998)). We include the dividend yield on the world equity index (in excess of the risk-free rate), the U.S. default premium measured by the yield differential between Moody's Baa and Aaa rated bonds, and the change in the U.S. term premium calculated as the difference between the yield on the ten-year U.S. Treasury note and the Federal Funds Rate.[44] The dividend yield is obtained from Datastream and the bond yields are taken from the website of the Federal Reserve System.[45]

Table 4.1 presents summary statistics over the period 1975:01-1998:12. Panel A, B, and C depict information on the summary statistics for the equity indices and the real exchange rates, the instrumental variables, and the nominal exchange rates and inflation differentials, respectively. The stock indices earn monthly excess returns ranging from 59 basis points for Japan to 117 basis points for the U.K. The skewness and especially the kurtosis generally show large deviations from the values of the normal distribution. The distribution of the excess returns on the U.K. stock index in particular exhibit very fat tails, which is primarily due to several extreme returns in 1975 (also documented by De Santis and Gérard (1998)). The Jarque-Bera test strongly rejects the assumption of normally distributed returns for all series. Real exchange rate returns are fairly close to zero over the sample period, except for the Japanese yen, which showed a substantial appreciation against the German mark in real terms. The standard deviation of all real exchange rates in the sample is substantial. As is noted by a number of previous studies (e.g. Rogoff (1996)), inflation differentials are considerably less volatile than nominal exchange rates. Panel D of Table 4.1 contains the unconditional correlations between stock index returns and real exchange rate returns. Correlations between equity returns are all positive and range from 0.283 to 0.550. Correlations between real exchange rates are all positive and smaller than 0.5. Stock index returns and real exchange rates are generally negatively correlated and assume values of up to –0.609. Unconditional correlations between equity returns and nominal exchange rate returns are negative and generally substantial, as indicated by Panel E. Equity returns do not strongly correlate with inflation differentials. Correlations are generally very close to zero, except for the inflation differential between Germany and the U.S. Finally, correlations between nominal exchange rate returns and inflation differentials are remarkably low, amounting to less than 0.1 with only one exception.

[44] In line with De Santis and Gérard (1998), we also estimated our model with the change in yield on the one-month euro-dollar deposit as an additional instrumental variable. Our optimization procedure becomes considerably less efficient due to the addition of this variable and hence we decided to omit it. However, the inclusion of this instrument in the information set does not materially affect our estimation results and does not statistically improve our specification. Unreported evidence on this issue is available from the authors.

[45] Federal Reserve System, homepage, http://www.fed.gov/ (accessed April 27, 2004).

Table 4.1
Summary statistics (1975-1998)

This table reports summary statistics for the asset excess returns expressed in German marks over the period 1975:01-1998:12. Equity indices are from Morgan Stanley Capital International (MSCI). Real exchange rates versus the German mark are constructed from nominal exchange rates and CPI indices obtained from International Financial Statistics (IFS). The one-month euro-mark deposit quoted in London is taken as the conditionally risk-free asset. All returns are in expressed in a percentage per month. J-B is the Jarque-Bera test statistic for normality. Q12 denotes the *p*-value of the Ljung-Box test statistic of order 12. *, **, *** denote significance at the 10%, 5%, and 1% significance levels, respectively.

	Mean	Median	St.Dev.	Skewness	Kurtosis	J-B	Q_{12}
PANEL A: SUMMARY STATISTICS OF EQUITY RETURNS AND REAL EXCHANGE RATE RETURNS							
MSCI Germany	0.698	0.803	5.380	-0.507	5.130	66.8***	15.4
MSCI France	0.874	0.918	6.459	0.007	4.177	16.6***	10.1
MSCI Japan	0.593	0.744	6.519	0.137	3.928	11.2***	10.0
MSCI U.K.	1.169	1.519	6.957	1.124	12.861	1227.5***	14.7
MSCI U.S.	0.854	1.028	5.429	-0.533	5.051	64.1***	9.3
MSCI World	0.710	0.894	4.570	-0.646	5.070	71.5***	19.0*
Real exchange rate France	-0.002	-0.094	1.178	1.247	9.654	606.0***	13.2
Real exchange rate Japan	-0.149	0.147	3.122	-0.409	3.857	16.2***	15.5
Real exchange rate U.K.	-0.073	-0.082	2.739	0.292	4.337	25.5***	12.2
Real exchange rate U.S.	0.019	0.072	3.286	-0.084	3.968	11.6***	12.6
PANEL B: SUMMARY STATISTICS OF INSTRUMENTS							
Dividend yield MSCI World	-0.349	-0.318	0.217	-1.104	4.759	95.6***	2095.2***
U.S. default premium	1.152	1.080	0.480	0.940	3.313	43.6***	2254.7***
Change in U.S. term premium	0.006	0.000	0.679	1.708	21.283	4151.0***	84.7***

Table 4.1 - *continued*

Summary statistics (1975-1998)

This table reports summary statistics for the excess returns over the period 1975:01-1998:12. J-B is the Jarque-Bera test statistic for normality. Q12 denotes the Ljung-Box test statistic of order 12. *, **, *** denote significance at the 10%, 5%, and 1% significance levels, respectively.

	Mean	**Median**	**St.Dev.**	**Skewness**	**Kurtosis**	**J-B**	**Q_{12}**
PANEL C: SUMMARY STATISTICS OF NOMINAL EXCHANGE RATES AND INFLATION DIFFERENTIALS							
Nominal exchange rate France	0.215	0.083	1.158	1.845	10.741	882.4***	25.1**
Nominal exchange rate Japan	-0.158	0.030	3.067	-0.449	3.821	17.7***	15.1
Nominal exchange rate U.K.	0.282	0.191	2.677	0.394	4.505	34.6***	11.0
Nominal exchange rate U.S.	0.181	0.244	3.291	-0.041	3.941	10.7***	11.2
Inflation differential France	-0.216	-0.194	0.414	-0.260	4.847	44.1***	404.5***
Inflation differential Japan	0.009	0.008	0.633	-0.544	4.027	26.9***	167.5***
Inflation differential U.K.	-0.353	-0.277	0.679	-1.118	9.135	511.7***	197.3***
Inflation differential U.S.	-0.161	-0.156	0.371	-0.209	6.462	146.0***	161.4***

Table 4.1 - *continued*

Summary statistics (1975-1998)

This table reports unconditional correlations of the (excess) returns over the period 1975:01-1998:12.

	MSCI Germany	**MSCI France**	**MSCI Japan**	**MSCI U.K.**	**MSCI U.S.**	**r.e.r. France**	**r.e.r. Japan**	**r.e.r. U.K.**	**r.e.r. U.S.**	**MSCI World**
PANEL D: UNCONDITIONAL CORRELATIONS BETWEEN EQUITY RETURNS AND REAL EXCHANGE RATE RETURNS										
MSCI Germany	1	0.550	0.283	0.412	0.414	0.006	-0.022	-0.081	-0.131	0.529
MSCI France		1	0.362	0.520	0.467	-0.281	-0.142	-0.153	-0.148	0.597
MSCI Japan			1	0.352	0.343	-0.092	-0.555	-0.206	-0.194	0.686
MSCI U.K.				1	0.535	-0.239	-0.179	-0.471	-0.233	0.674
MSCI U.S.					1	-0.163	-0.220	-0.258	-0.609	0.880
Real exchange rate France						1	0.229	0.314	0.256	-0.170
Real exchange rate Japan							1	0.263	0.401	-0.365
Real exchange rate U.K.								1	0.401	-0.343
Real exchange rate U.S.									1	-0.494
MSCI World										1

	n.e.r. France	**n.e.r. Japan**	**n.e.r. U.K.**	**n.e.r. U.S.**	**infl. diff. Fra**	**infl. diff. U.K.**	**infl. diff. Jap**	**infl. diff. U.S.**
PANEL E: UNCONDITIONAL CORRELATIONS BETWEEN EQUITY RETURNS, NOMINAL EXCHANGE RATE RETURNS, AND INFLATION DIFFERENTIALS								
MSCI Germany	-0.008	-0.028	-0.092	-0.142	0.040	0.029	0.032	0.096
MSCI France	-0.281	-0.145	-0.141	-0.150	-0.017	0.000	-0.064	0.015
MSCI Japan	-0.090	-0.566	-0.213	-0.204	-0.011	0.007	0.007	0.088
MSCI U.K.	-0.252	-0.183	-0.461	-0.244	0.021	0.002	-0.090	0.101
MSCI U.S.	-0.189	-0.239	-0.275	-0.623	0.061	0.068	0.037	0.121
MSCI World	-0.190	-0.384	-0.355	-0.509	0.044	0.053	0.011	0.138
Nominal exchange rate France					-0.121	-0.030	0.019	0.000
Nominal exchange rate Japan					0.023	-0.018	-0.032	-0.011
Nominal exchange rate U.K.					-0.042	-0.053	-0.019	0.046
Nominal exchange rate U.S.					-0.036	-0.087	-0.093	-0.051

4.5 Empirical results

This section presents estimates and tests of two different models. First, we estimate the model presented by equation (4.2). In this version of the ICAPM, the assumption that domestic inflation rates expressed in local currency are non-stochastic is relaxed, and asset returns depend on their covariance with the global market portfolio and real exchange rate risk factors. Second, we provide estimates and statistical tests of the model in equation (4.3). This model posits that asset returns depend on global market risk, nominal exchange rate risk, as well as inflation risk. Both model specifications are considered in their conditional version, implying that covariances are allowed to vary over time.

Our empirical analysis uses five country stock indices (Germany, France, Japan, the U.K., and the U.S.), four real exchange rate indices, and the world market index. All returns are measured in German marks and hence we consider the real exchange rate risk of all four remaining countries in the sample versus the German mark. Nominal exchange rates are also measured versus the German mark, while the inflation rate differentials are defined as the difference between the inflation rate of the four remaining countries (France, Japan, the U.K., and the U.S.) and the German inflation rate. As abundant evidence in the academic asset pricing literature demonstrates that prices of risk exhibit time-varying behavior, we let the world prices of risk vary over time by conditioning on a number of variables that proxy for the state of the economy. For model (2), the functional forms for the relation between the prices of risk (market and real exchange rate risk) and the instrumental variables Z_{t-1} are given by equations (4.5) and (4.6). For our implementation of model (4.3), the corresponding functional firms are reflected in equations (4.10), (4.11), and (4.12) for market, nominal exchange rate, and inflation risk respectively. Testing the hypothesis of time-variation of the prices of risk is straightforward within our framework.

Table 4.2 presents the estimation results for the ICAPM with real exchange rate risk, as denoted by equation (4.4). We examine the period 1975:01-1998:12, as the adoption of the euro in January 1999 instigated a structural break in the (real) exchange rates (primarily between Germany and France). Section 4.6 addresses this issue in more detail. Panel A of Table 4.2 shows the point estimates and the standard errors of the mean equation parameters and Panel B depicts the estimates of the (conditional) covariance equation parameters. Several of these parameters (all of the covariance process) are significant in isolation. More interesting, however, are the specification tests that assess the significance of a number of parameters simultaneously. For each of the five world prices of risk, we performed a likelihood-ratio test in order to investigate (i) whether the prices of risk are constant or time varying and (ii) whether the prices of risk are significantly different from zero. Concerning the world prices of real exchange rate risk, we apply the tests to all prices of risk simultaneously as well as separately for each real exchange rate in the sample. The results of the specification tests are reflected in Panel C of Table 4.2.

Table 4.2

QML estimates of the conditional ICAPM with time-varying prices of market and real exchange rate risk (1975-1998)

This table depicts quasi-maximum likelihood estimation results of the conditional ICAPM with time-varying prices of risk over the period 1975:01-1998:12. Equity indices are from Morgan Stanley Capital International (MSCI). Real exchange rates versus the German mark are constructed from nominal exchange rates and CPI indices obtained from International Financial Statistics (IFS). The one-month euro-mark deposit quoted in London is taken as the conditionally risk-free asset. Each mean equation relates the asset excess return r_{it} to the covariance with global equity returns cov(r_{it}, r_{mt}) and the covariance with nominal exchange rate returns cov(r_{it}, s_{lt}). The prices of risk are functions of instruments in Z_{t-1}, which proxy for the information set that investors use in choosing their portfolios. The instruments include a constant, the dividend yield on the MSCI world index in excess of the one-month euro-dollar rate (WorldDY), the default premium in the U.S. (USDP), and the change in the U.S. term premium (ΔUSTP).

PANEL A: PARAMETER ESTIMATES – MEAN EQUATIONS

	C	**s.e.**	**WorldDY**	**s.e.**	**USDP**	**s.e.**	**ΔUSTP**	**s.e.**
a. Price of market risk								
κ_m	-3.706	0.127	1.490	0.164	1.091	0.082	0.111	0.022
b. Prices of real e.r. risk								
κ_{FRA}	-0.140	0.161	-0.162	0.294	0.058	0.132	0.001	0.068
κ_{UK}	-0.132	0.073	0.286	0.147	0.202	0.063	-0.088	0.036
κ_{JAP}	0.023	0.060	-0.285	0.106	-0.119	0.050	0.054	0.033
κ_{US}	0.129	0.052	0.139	0.120	-0.039	0.046	0.006	0.033

PANEL B: PARAMETER ESTIMATES – COVARIANCE PROCESS

	MSCI Ger	**MSCI Fra**	**MSCI U.K.**	**MSCI Jap**	**MSCI U.S.**	**r.e.r. Fra**	**r.e.r. U.K.**	**r.e.r. Jap**	**r.e.r. U.S.**	**MSCI World**
a	0.186	0.172	0.233	0.213	0.232	0.145	0.182	0.208	0.193	0.206
s.e.	0.032	0.028	0.020	0.021	0.021	0.023	0.072	0.041	0.038	0.017
b	0.965	0.981	0.960	0.957	0.950	0.988	0.822	0.926	0.932	0.958
s.e.	0.014	0.009	0.008	0.010	0.010	0.007	0.089	0.025	0.028	0.008

Table 4.2 - *continued*

QML estimates of the conditional ICAPM with time-varying prices of market and real exchange rate risk (1975-1998)

Panel C of this table depicts the results of a number of specification tests of the conditional ICAPM with time-varying prices of risk over the period 1975:01-1998:12. *, **, *** denote significance at the 10%, 5%, and 1% significance levels, respectively.

PANEL C: SPECIFICATION TESTS				
Hypothesis	**LR-test**	**df**	***p*-value**	
H_0: The price of market risk is constant	7.579	3	0.056	*
H_0: The price of market risk is equal to zero	19.602	4	0.001	***
H_0: The price of real exchange rate risk is constant	24.818	12	0.016	**
Real exchange rate France	1.072	3	0.784	
Real exchange rate U.K.	13.757	3	0.003	***
Real exchange rate Japan	10.472	3	0.015	**
Real exchange rate U.S.	3.761	3	0.289	
H_0: The price of real exchange rate risk is equal to zero	27.049	16	0.041	**
Real exchange rate France	1.073	4	0.899	
Real exchange rate U.K.	13.762	4	0.008	***
Real exchange rate Japan	10.778	4	0.029	**
Real exchange rate U.S.	5.973	4	0.201	

The first two tests in Panel C focus on the world price of market risk. This price of risk is significantly different from zero, while we reject the hypothesis that the world price of market risk is constant at the 10% significance level. This is in line with the results of Dumas and Solnik (1995) and De Santis and Gerard (1998). All other specification tests in Panel C assess the prices of real exchange rate risk. The tests show that these prices of risk are jointly time varying (p-value of 0.016) and reject the hypothesis of no real exchange rate risk at the 95 percent confidence level (p-value of 0.041). A more detailed perspective on the importance of real exchange rate risk is given by the specification tests for each real exchange rate separately. The evidence indicates that only the real exchange rate of Japan and the U.K. have a significant impact on the pricing of the assets under consideration. The prices of the real exchange rates of the French franc and the U.S. dollar versus the German mark are insignificant. The null-hypothesis that the prices of real exchange rate risk are constant is strongly rejected for Japan and the U.K., but not for the other countries.

Previous empirical tests of the ICAPM assume that the inflation rate is non-stochastic and hence only incorporate nominal exchange rate risk. The world prices of nominal exchange rate risk are typically highly significant in these studies. Table 4.2 shows, however, that the prices of exchange rate risk related to France and, more surprisingly, the U.S. are not significantly different from zero. In our empirical study, these prices of risk are associated with real exchange rate risk and hence consist of two components: nominal exchange rate risk and inflation risk. A relevant issue is whether these components of the price of currency risk partially offset each other, notably for France and the U.S.

In order to establish the sign and relative magnitude of inflation risk and nominal exchange rate risk premia, we extend our analysis to include both sources of risk separately. The total number of excess returns included in the analysis is then equal to $M' = N + L + L + 1$ assets, consisting of N local stock market indices, L nominal exchange rate factors, L inflation rate factors, and the world market index. All prices of risk factors are assumed to be time-varying and depend on the instruments Z_t. The empirical specification of the model is given by equations (4.9) to (4.12). Table 4.3 presents the results of the analysis. The estimates of the mean equation are depicted in Panel A. Comparing the nominal exchange rate risk parameter estimates with the inflation rate risk parameters, we observe a number of differences. First, the parameters corresponding to the inflation rate risk are generally higher in absolute terms than the value of the corresponding nominal exchange rate risk parameters. Second, the prices of nominal exchange rate and inflation risk often exhibit opposite sensitivities to the instruments. Only the coefficients on the world dividend yield have the same sign for all nominal exchange rate – inflation rate combinations (negative for France and Japan and positive for the U.K. and the U.S.). The estimates of the variance equation are presented in Panel B of Table 4.3. The parameter estimates of a are consistently higher for the nominal exchange rates than for the inflation risk factors. It is also clear that the standard errors for the inflation risk factors are lower than the standard errors for the nominal exchange rate risk factors. Finally, inflation risk factors show a higher persistence denoted by an estimate for b that is very close to 1.

Panel C of Table 4.3 displays the results of a number of specification tests that assess the significance and time-variation of the prices of risk. In line with the results in Table 4.2, we strongly reject the hypotheses that the price of market risk is constant over time and equal to zero. The prices of nominal exchange are also highly significantly different from zero, both jointly and for each individual nominal exchange rate in the sample. In contrast to our findings in Table 4.2, French and U.S. currency risk thus also carry a significant price of risk in this model. This is consistent with previous empirical research detecting priced nominal exchange rate risk factors. The most striking results in Table 4.3, however, concern inflation risk. For all inflation risk factors (jointly and separately), the hypothesis that their prices of risk are equal to zero is rejected at any conventional significance level. This indicates that, despite the fact that the variance of the inflation differentials is substantially lower than the variance of the nominal exchange rates, inflation risk constitutes a significant priced risk factor in international equity returns. Finally, we find strong evidence against a specification of the model in which the prices of nominal exchange rate and inflation risk are constant.

While both the prices of nominal exchange rate risk and the prices of inflation risk in our model are significant in statistical terms, the contribution of either or both sources of risk to asset returns could be small in economic terms. Figure 4.1 presents plots of the nine different prices of risk in our model over the period 1975-1998. The graphs also contain a line representing the average price of risk over the sample period as well as the Hodrick-Prescott filtered prices. The latter can be used to obtain an insight in the general trend over time, as the point estimates are subject to estimation error. (Note that the scaling differs for the graphs of the prices of market, nominal exchange rate, and inflation risk.) All prices of risk exhibit substantial variation over time. The graph of the world price of market risk is very similar to the plot depicted in Figure 1 of De Santis and Gérard (1998), with peaks in the mid 1970s, in the year 1980, and around 1983. The average price of market risk in our model is 0.075, which is substantially higher than the estimate of De Santis and Gérard. A plausible explanation for this is that the world market portfolio in the ICAPM without inflation risk factors partially absorbs the prices of inflation risk, which are generally negative in our sample. The graphs of the prices of nominal exchange rate risk resemble the general patterns observed by De Santis and Gérard (1998). All exchange rate risk prices seem to matter for international asset pricing. The sample means are equal to 0.154 for France, –0.021 for Japan, 0.066 for the U.K., and 0.0087 for the U.S. While the mean values are relatively close to zero, all four prices of risk attain considerable higher values in some periods and all assume both positive and negative values over the

Table 4.3

QML estimates of the conditional model with time-varying prices of market, nominal exchange rate, and inflation risk (1975-1998)

This table depicts quasi-maximum likelihood estimation results of the conditional MODEL with time-varying prices of risk over the period 1975:01-1998:12. Equity indices are from Morgan Stanley Capital International (MSCI). Real exchange rates versus the German mark are constructed from nominal exchange rates and CPI indices obtained from International Financial Statistics (IFS). The one-month euro-mark deposit quoted in London is taken as the conditionally risk-free asset. Each mean equation relates the asset excess return r_{it} to the covariance with global equity returns cov(r_{it}, r_{mt}) and the covariance with nominal exchange rate returns cov(r_{it}, s_{lt}). The prices of risk are functions of instruments in Z_{t-1}, which proxy for the information set that investors use in choosing their portfolios. The instruments include a constant, the dividend yield on the MSCI world index in excess of the one-month euro-dollar rate (WorldDY), the default premium in the U.S. (USDP), and the change in the U.S. term premium (ΔUSTP).

PANEL A: PARAMETER ESTIMATES – MEAN EQUATIONS

	C	**s.e.**	**WorldDY**	**s.e.**	**USDP**	**s.e.**	**ΔUSTP**	**s.e.**
a. Price of market risk								
κ_m	-3.150	0.105	1.072	0.162	0.747	0.072	0.091	0.020
b. Prices of nominal e.r. risk								
λ_{FRA}	-0.125	0.116	-0.136	0.277	0.201	0.124	0.015	0.083
λ_{UK}	-0.083	0.069	0.232	0.150	0.200	0.060	-0.076	0.038
λ_{JAP}	0.017	0.055	-0.241	0.117	-0.106	0.047	0.068	0.036
λ_{US}	0.161	0.048	0.113	0.121	-0.098	0.042	-0.021	0.037
c. Prices of inflation risk								
φ_{FRA}	3.912	0.610	-0.150	1.224	-4.081	0.645	-0.358	0.400
φ_{UK}	-0.825	0.243	0.035	0.594	0.131	0.291	-0.364	0.212
φ_{JAP}	0.315	0.350	-0.494	0.607	0.307	0.335	-0.245	0.138
φ_{US}	-3.226	0.633	3.891	1.361	3.338	0.647	0.911	0.312

Table 4.3 - *continued*

QML estimates of the conditional model with time-varying prices of market, nominal exchange rate, and inflation risk (1975-1998)

Panel B of this table depicts quasi-maximum likelihood estimation results of the conditional model with time-varying prices of risk over the period 1975:01-1998:12. Panel C of this table depicts the results of a number of specification tests of the conditional model with time-varying prices of risk over the period 1975:01-1998:12. *, **, *** denote significance at the 10%, 5%, and 1% significance levels, respectively.

PANEL B: PARAMETER ESTIMATES – COVARIANCE PROCESS

	MSCI Ger	**MSCI Fra**	**MSCI U.K.**	**MSCI Jap**	**MSCI U.S.**	**n.e.r. Fra**	**n.e.r. U.K.**	**n.e.r. Jap**	**n.e.r. U.S.**	**infl. Fra**	**infl. U.K.**	**infl. Jap**	**infl. U.S.**	**MSCI World**
a	0.188	0.138	0.216	0.196	0.215	0.168	0.264	0.200	0.186	0.080	0.058	-0.078	0.024	0.189
s.e.	0.033	0.015	0.020	0.020	0.021	0.026	0.080	0.038	0.034	0.012	0.029	0.022	0.030	0.016
b	0.956	0.992	0.963	0.961	0.953	0.981	0.663	0.938	0.932	0.994	0.991	0.995	0.916	0.960
s.e.	0.016	0.004	0.008	0.009	0.011	0.008	0.121	0.022	0.025	0.004	0.018	0.006	0.170	0.008

PANEL C: SPECIFICATION TESTS

Hypothesis	**LR-test**	**df**	***p*-value**	
H_0: The price of market risk is constant	10.003	3	0.019	**
H_0: The price of market risk is equal to zero	24.170	4	0.000	***
H_0: The price of nominal exchange rate risk is constant	36.511	12	0.000	***
H_0: The price of nominal exchange rate risk is equal to zero	53.957	16	0.000	***
Nominal exchange rate France	15.146	4	0.004	***
Nominal exchange rate U.K.	23.388	4	0.000	***
Nominal exchange rate Japan	11.584	4	0.021	**
Nominal exchange rate U.S.	13.468	4	0.009	***
H0: The price of inflation risk is constant	118.495	12	0.000	***
H0: The price of inflation risk is equal to zero	227.076	16	0.000	***
Inflation differential France	87.439	4	0.000	***
Inflation differential U.K.	41.219	4	0.000	***
Inflation differential Japan	60.208	4	0.000	***
Inflation differential U.S.	58.831	4	0.000	***

Figure 4.1
The prices of market, nominal exchange rate, and inflation risk

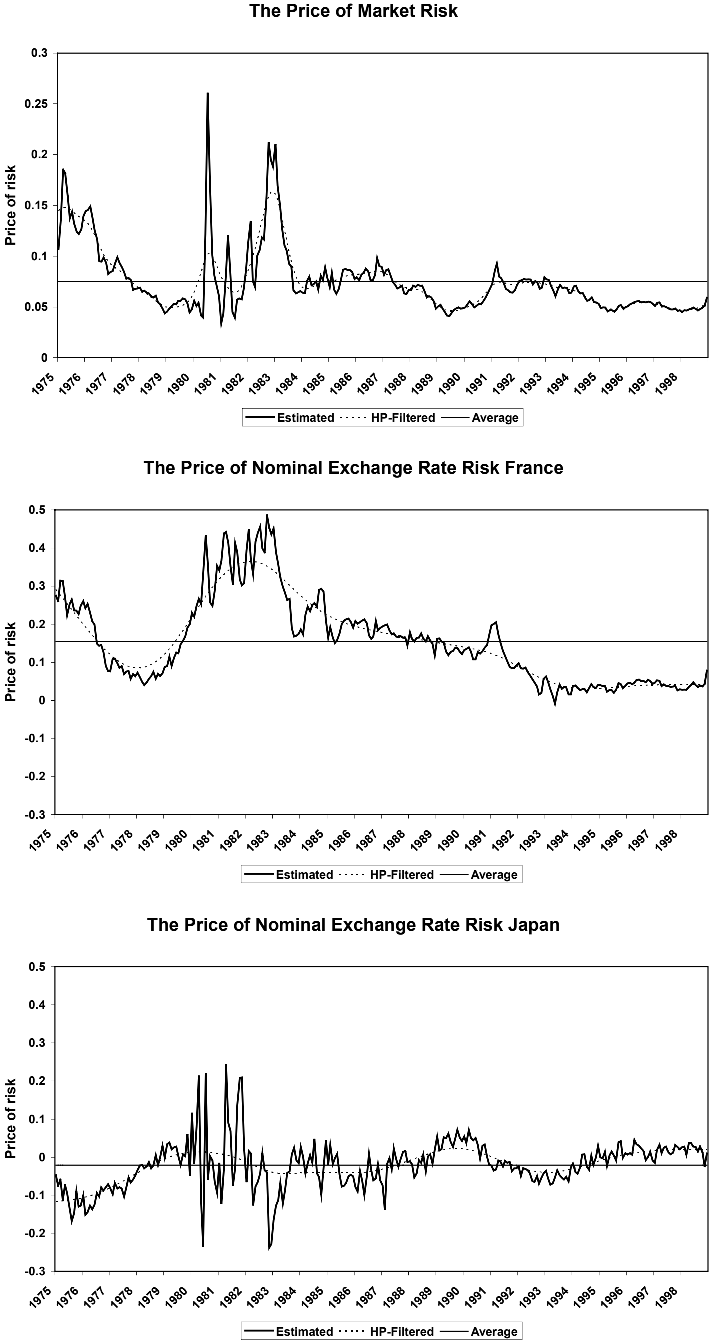
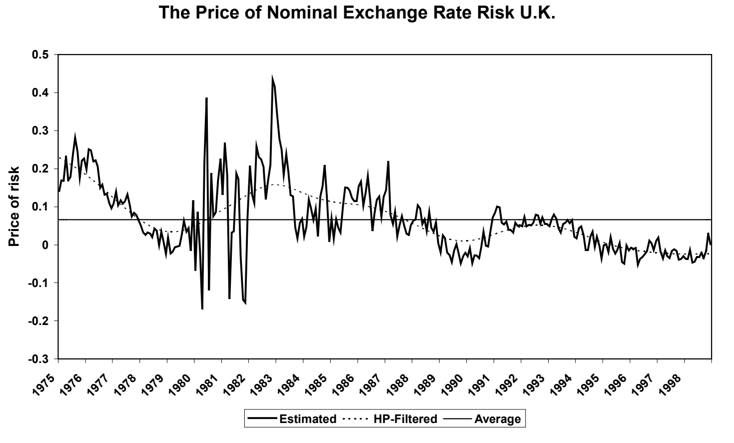
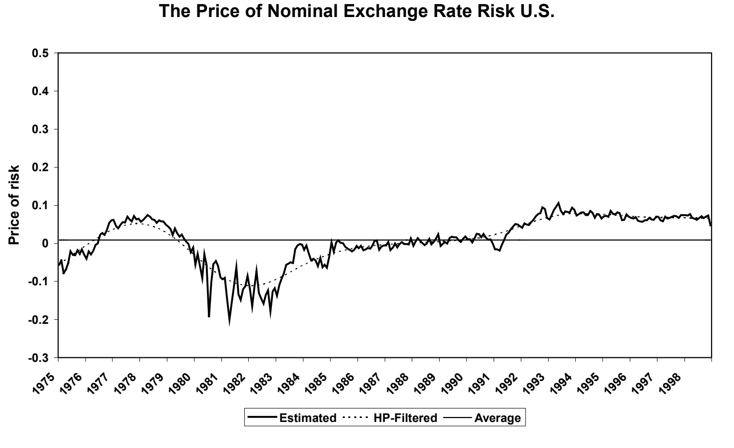


Figure 4.1 - *continued*
The prices of market, nominal exchange rate, and inflation risk





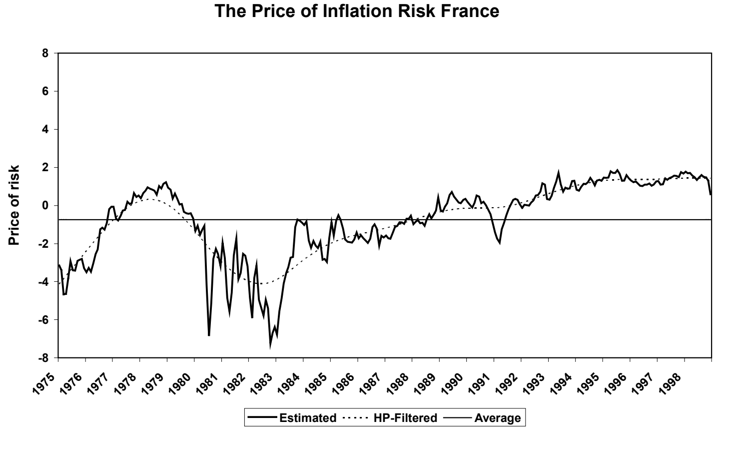
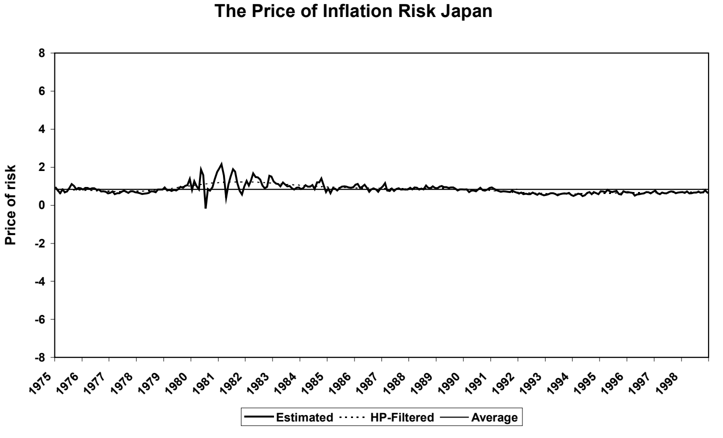
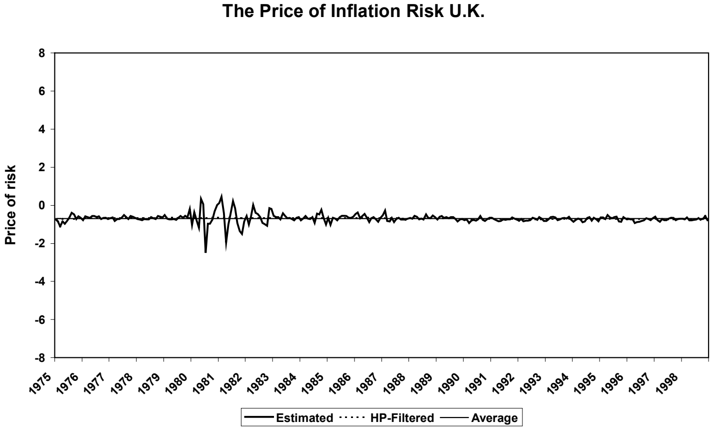
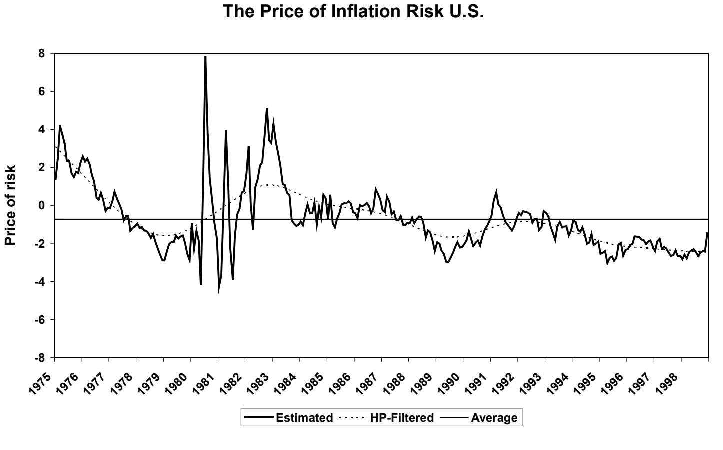


Figure 4.1 - *continued*
The prices of market, nominal exchange rate, and inflation risk





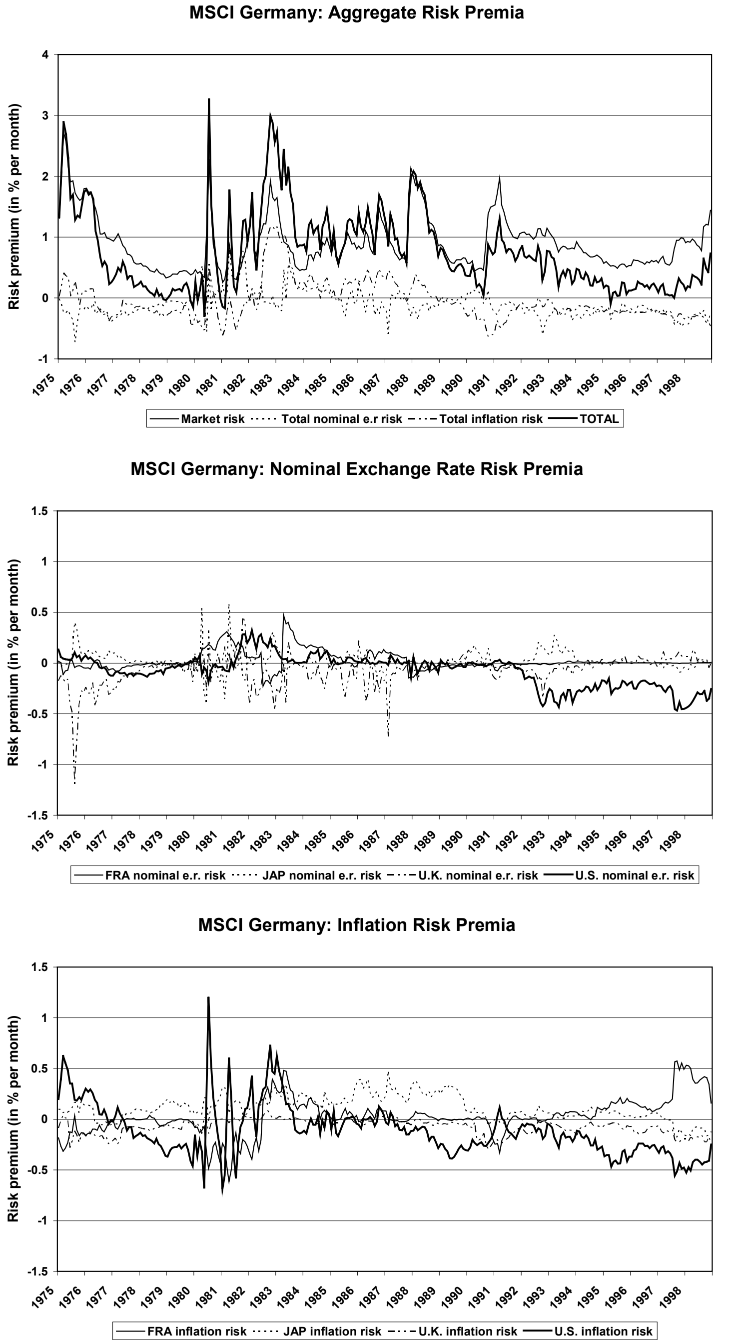


sample period (although the price of nominal exchange rate risk related to the French franc is virtually always positive). The prices of inflation risk are strikingly large. Averages over the sample period amount to –0.752 for France, 0.842 for Japan, -0.687 for the U.K., and –0.725 for the U.S. However, these large prices of risk are to a large extent counterbalanced by very small covariances between asset returns and inflation risk factors. As a comparison, the unconditional covariance between German equity returns and the U.S. inflation risk factor is equal to 0.145, while the covariance between German equity returns and the world market returns is 12.743. Nevertheless, despite the limited (co)variance of inflation differentials, the high prices of risk are likely to produce substantial inflation risk premia in asset returns.

In order to assess the importance of inflation and nominal exchange rate risk premia relative to each other and relative to the global market factor, we decompose the expected asset returns in our sample into the risk premia related to the various sources of risk. The (time-varying) premium for market risk for asset *i* can be computed as the product of the price of market risk $\delta_{m,t-1}$ and the conditional covariance $cov[\, r_{it} \,,\, r_{mt} \mid \Omega_{t-1} \,]$. Similarly, the *l* nominal exchange rate risk premia for asset *i* can be estimated with $\varphi_{l,t-1} \times cov[\, r_{it} \,,\, s_{lt} \mid \Omega_{t-1} \,]$ and the term $\gamma_{l,t-1} \times cov[\, r_{it} \,,\, \pi_{lt} - \pi_{0t} \mid \Omega_{t-1} \,]$ constitutes an estimate of the inflation risk premia for asset *i*. Figure 4.2 depicts the development of the risk premia for German equity over time. The top panel gives an overview of the aggregate contributions of market, nominal exchange rate, and inflation risk to expected Germany equity returns. The middle and bottom panel depict individual nominal exchange rate and inflation risk premia related to France, Japan, the U.K., and the U.S. (Note that the scaling of the middle and bottom panels is different from the top panel.) A number of important observations emerge. Global market risk is the dominant component of the total risk premium on Germany equity, amounting to around 90 basis points per month on average over the period 1975-1998. This risk premium is strongly time varying as both the price of market risk and the conditional covariance between German equity returns and returns on the global market index exhibit considerable fluctuations.

The aggregate premium for nominal risk exchange rate risk is generally negative. The average value computed over the entire sample is –0.104. As the sample averages of conditional risk premia can be expected to approximate their unconditional values, this suggests that an unconditional analysis of nominal exchange rate risk would indicate that the premium for currency risk is relatively modest. However, the premium was markedly negative in most of the 1970s and 1990s, but strongly positive in the early and mid 1980s. The sample average of the absolute value of the premium is almost 20 basis points per month or roughly 2.4 percent per annum, while occasionally values of up to 70 basis points per month are reached (both positive and negative). Moreover, the aggregate currency risk premium disregards possible offsetting effects across the four nominal exchange rates in the sample. The middle panel of Figure 4.2 demonstrates that the contribution of every

Figure 4.2
Estimated risk premia decomposition: MSCI Germany



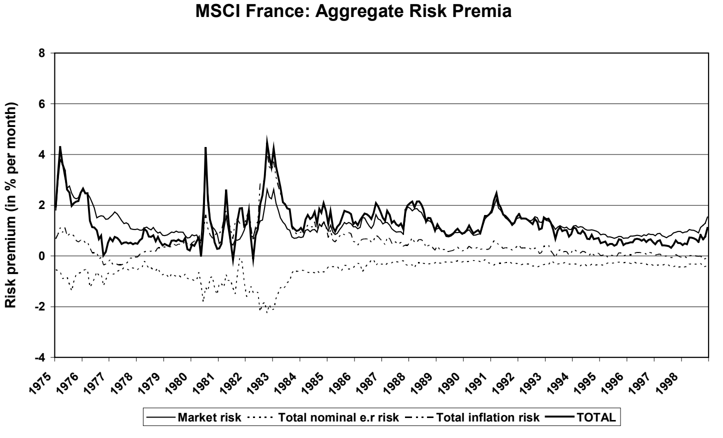
individual nominal exchange rate has been economically substantial for prolonged periods of time. The sample averages of the risk premia related to the French franc and the Japanese yen are approximately 5 basis points per month, but both sources of risk carried a substantial premium in German equity returns in the 1980s, reaching values of up to 50 basis points per month. The premium for U.K. risk was highly negative in the 1970s, large and volatile in the early 1980s, and consistently negative again in the late 1980s. Nominal exchange rate risk related to the U.S. became the principal source of currency risk in the 1990s, with a negative risk premium of roughly 27 basis points per month over the period 1992-1998.

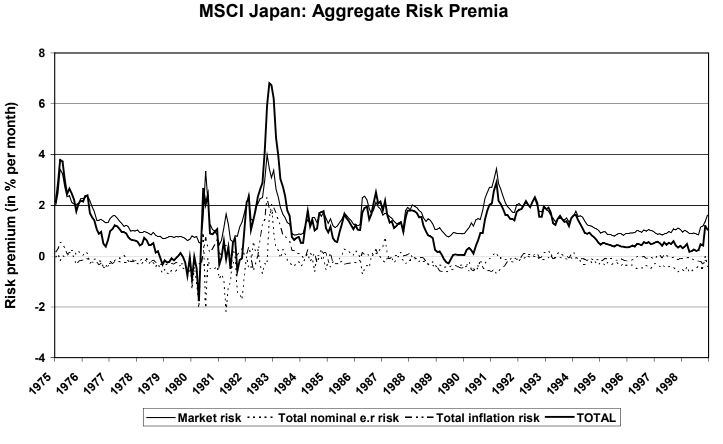
Figure 4.2 shows that the premia for inflation risk in the returns in the MSCI Germany index were economically substantial over the period 1975-1998. The sample average of the aggregate risk premium of –4.6 basis points per month is relatively small, but the average absolute value is equal to 26 basis points, which is even somewhat higher than the aggregate premium for currency risk. The aggregate premium for inflation risk was negative for most of the 1970s and 1990s, but substantial and positive in the 1980s (averaging more than 30 basis points per month in the years 1982-1988). In the mid 1970s and 1980s the premia for inflation risk and nominal exchange rate risk generally had opposite signs, but both turned negative around 1990. The bottom panel of Table 4.2 illustrates the cross-sectional differences in inflation risk premia. The U.K. premium assumed small negative values for almost the entire sample period. The inflation risk premium for Japan was positive in most months with an average absolute value of 13 basis points over the sample period. This premium was large in the 1980s, but vanished during the 1990s. Investors in the German equity index generally received a positive risk premium for inflation risk related to France, but the premium was negative in 1975-1977 and especially in the early 1980s, attaining a value of –61 basis points in April 1981. It is interesting to see that the French inflation risk premium has picked up in the late 1990s. The most important source of inflation risk in German equity returns clearly was the risk associated with the inflation differential with the U.S. The sample mean of the absolute premium amounts to no less than 22 basis points on a monthly basis, or over 2.5 percent per year. Since the mid 1980s, the premium for U.S. inflation risk has generally been negative and relatively steady around –0.2. U.S. inflation risk carried a large and positive premium in the mid 1970s and was highly volatile in the first half of the 1980s. In this time period, the U.S. inflation risk component in expected returns on the MSCI Germany index was occasionally of the same order of magnitude as global market risk.

Figure 4.3 depicts the market risk, nominal exchange rate risk, and inflation risk components in the expected returns on equity indices in France, Japan, the U.K., the U.S., as well as the world market index. Although the total equity premia for the equity indices is to a large extent explained by the premium for market risk, both aggregate nominal exchange rate risk premia and aggregate inflation risk premia are often large. For France the average market risk premium was 1.249 percent per month and the mean absolute nominal exchange rate and inflation risk premia amounted to 0.562 percent and 0.565 percent, respectively. The nominal exchange rate risk premium is always negative, while inflation risk generally bears a positive risk premium. Both sources of risk seem to be more important in the first half of the sample period than in the second half, although the market risk premium also diminishes in the 1990s. There are considerable differences in the relative importance of currency and inflation risk among the other countries in the sample. For the U.K. in particular nominal exchange rate risk and inflation risk represent very significant parts of the total risk premium. The average absolute risk premium for inflation risk equals more than 35 basis points per month for U.K. equity. For Japan and the U.S. these risk premia are less important, but nevertheless nontrivial (mean absolute values of, respectively, 27 and 22 basis points per month). The graph for the world market index reflects the characteristics of all markets. The exchange rate and inflation risk premia are generally of opposite sign for France and the U.K., while they often reinforce each other for Japan and the U.S. It is important to note that the graphs in Figure 4.3 do not give insight in the magnitude and development of individual currency and inflation risk premia. As an example, the aggregate inflation risk premium for the U.S. is relatively small, but individual inflation risk premia are substantial. Sample averages of (absolute) inflation risk premia incorporated in U.S. equity returns are equal to, respectively, –0.118 (0.273) percent per month for France, 0.202 (0.203) for Japan, –0.119 (0.121) for the U.K., and –0.145 (0.292) for the U.S.

The evidence in Table 4.3 and in Figures 4.1-4.3 strongly indicates that inflation differentials between countries entail nontrivial priced risk factors in asset returns. This constitutes strong evidence against the Solnik-Sercu assumption that domestic inflation is non-random. An important issue is why inflation risk premia are comparable in size to nominal exchange rate risk premia, while the time-series volatility of inflation differentials is notably smaller than nominal exchange rate volatility. A plausible answer to this question is that hedging inflation risk is much more complicated than hedging against nominal exchange rate fluctuations. Currency risk can be hedged easily and cheaply using exchange-traded financial products (such as options and futures) on generally very liquid markets. The most straightforward way to hedge inflation risk is through index-linked bonds. However, as noted by e.g. Evans (1998), these bonds do not form a perfect hedge against inflation risk. Moreover, they are only available in a small number of countries. The findings presented in this section suggest that, as a result, inflation risk can be identified as a distinct and important source of systematic risk in asset returns. This conclusion could have important implications for asset pricing in countries between which no nominal exchange rates exist, but inflation rates do differ. The recognition of inflation risk as a separate source of priced risk could be of vital importance in the absence of

Figure 4.3
Estimated risk premia decomposition: MSCI equity indices





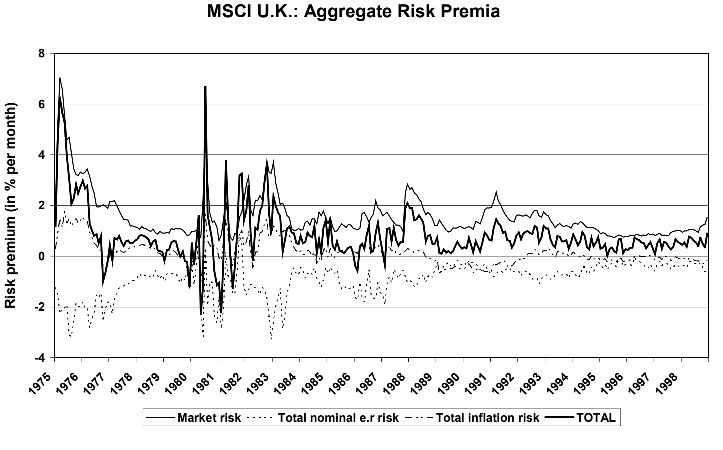
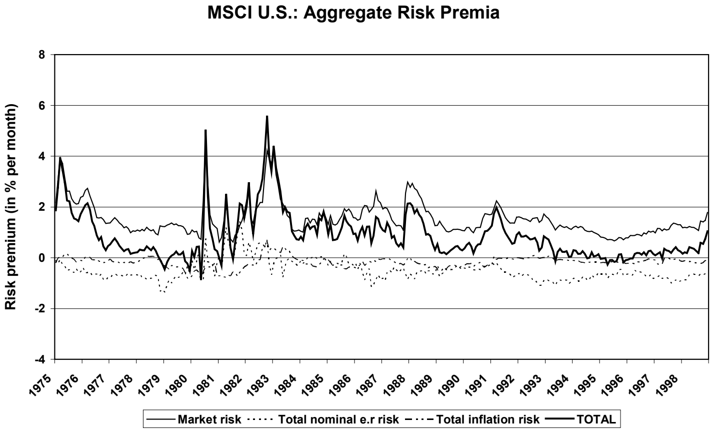
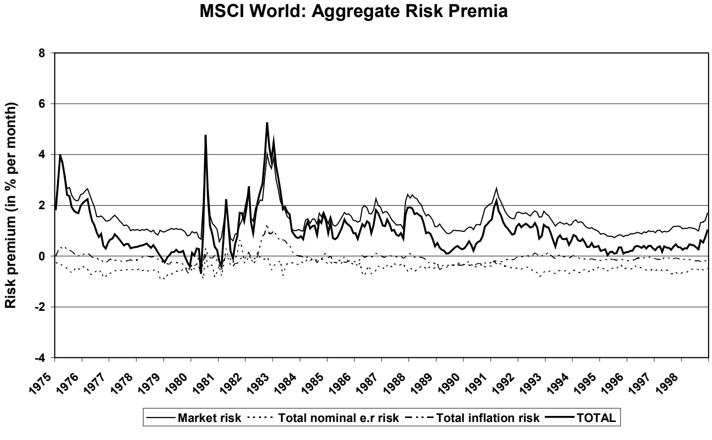


Figure 4.3 - *continued*
Estimated risk premia decomposition: MSCI equity indices





nominal exchange rate risk. The next section assesses the significance of inflation risk in Europe after the introduction of the euro in 1999.

4.6 The termination of nominal exchange risk in the euro area

In this section we apply the model introduced in section 4.2 in a setting in which nominal exchange rate risk has disappeared. Since the establishment of the EMU at the beginning of 1999, nominal exchange rates have been fixed among euro area countries. While this obviously implies that nominal exchange rate risk between euro area countries no longer carries a price, inflation differentials between these countries may still produce non-zero prices of inflation risk. This would have important implications for asset pricing. This section presents estimates and tests of the model incorporating nominal exchange rate and inflation risk depicted in equation (4.3) for asset returns in France, Germany, Japan, the U.K., and the U.S. over the period 1975:01-2003:12. As studying the euro area in isolation could lead to biases due to the fact that non-EMU sources of currency risk are neglected, we also include other countries and currencies in the analysis. At the same time, we need to restrict the total number of countries analyzed, because the incorporation of more assets and risk factors hampers the estimation procedure considerably. Hence, our analysis focuses on the price of inflation risk related to inflation differentials between France and Germany.[46] Unfortunately, estimating the model over the post-euro period is not feasible, as the number of parameters to be estimated requires a substantial time-series length. Estimating the model over the full period 1975-2003 raises a challenge for the empirical implementation of the model, because the nominal exchange rate of the French franc versus the German mark experiences a structural break in 1999. This holds especially for estimating the covariance matrix, as the volatility of the concerning variable becomes zero by definition after 1998. We apply an adaptation of the methodology of De Santis and Gérard (1998) in order to deal with this issue. A detailed description of the methodology is given in Appendix 4.A.

Table 4.4 presents the results of several specification tests of the model estimated over the period 1975-2003.[47] The world price of market risk is highly significant, although the hypothesis that this price of risk is constant over time is no longer rejected. We find some evidence for statistically significant prices of risk for all four nominal exchange rates in the sample. The evidence is strong for the exchange rate of the French franc versus the German mark, but slightly weaker for the other currencies in the sample. A specification of the model in which the prices of nominal exchange rate risk are unconditional is clearly rejected. Consistent with the results in the previous section, inflation risk factors carry highly significant prices of risk, both jointly and individually. Both the hypotheses that the prices of inflation risk are equal to zero and that the prices are constant over time are rejected at any conventional significance level. Most interesting, however, is to examine the price of inflation risk and especially of the inflation differential of France versus Germany. Figure 4.4 shows this price of inflation risk over the entire sample period 1975-

[46] Unreported results show that similar findings are obtained when we estimate the model with data for other European countries (e.g. Italy or the Netherlands) instead of France. We bias our results against finding significant intra-EMU inflation risk after the introduction of the euro by choosing a country that is economically closely integrated with Germany. The results are available from the authors.

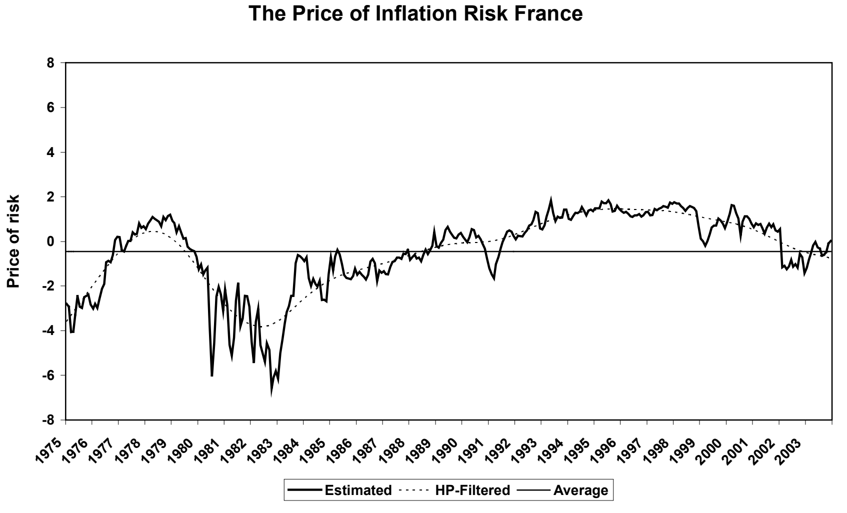
[47] Naturally, the estimation results are very similar to those reported in table 3, as the samples largely overlap. In order to conserve space, the parameter estimates of the model are not included in the table. They are available from the authors.

Table 4.4
QML estimates of the conditional model with time-varying prices of market, nominal exchange rate, and inflation risk (1975-2003)

This table depicts the results of a number of specification tests of the conditional model with time-varying prices of risk over the period 1975:01-1998:12. The model is estimated using quasi-maximum likelihood estimation. Equity indices are from Morgan Stanley Capital International (MSCI). Real exchange rates versus the German mark are constructed from nominal exchange rates and CPI indices obtained from International Financial Statistics (IFS). The one-month euro-mark deposit quoted in London is taken as the conditionally risk-free asset. Each mean equation relates the asset excess return r_{it} to the covariance with global equity returns cov(r_{it}, r_{mt}) and the covariance with nominal exchange rate returns cov(r_{it}, s_{lt}). The prices of risk are functions of instruments in Z_{t-1}, which proxy for the information set that investors use in choosing their portfolios. The instruments include a constant, the dividend yield on the MSCI world index in excess of the one-month euro-dollar rate (WorldDY), the default premium in the U.S. (USDP), and the change in the U.S. term premium (ΔUSTP). *, **, *** denote significance at the 10%, 5%, and 1% significance levels, respectively.

Hypothesis	LR-test	df	*p*-value	
H_0: The price of market risk is constant	2.321	3	0.508	
H_0: The price of market risk is equal to zero	15.868	4	0.003	***
H_0: The price of nominal exchange rate risk is constant	30.488	12	0.002	***
H_0: The price of nominal exchange rate risk is equal to zero	46.215	16	0.000	***
Nominal exchange rate France	18.358	4	0.001	***
Nominal exchange rate U.K.	11.414	4	0.022	**
Nominal exchange rate Japan	7.878	4	0.096	*
Nominal exchange rate U.S.	10.271	4	0.036	**
H0: The price of inflation risk is constant	111.840	12	0.000	***
H0: The price of inflation risk is equal to zero	232.662	16	0.000	***
Inflation differential France	84.849	4	0.000	***
Inflation differential U.K.	45.276	4	0.000	***
Inflation differential Japan	70.047	4	0.000	***
Inflation differential U.S.	56.932	4	0.000	***

Figure 4.4
The price of inflation risk over the full sample period 1975-2003



2003. The absolute level of the price of inflation risk in 1999-2003 does not appear to be notably lower than in the period before the introduction of the common currency (except for the high prices in the early 1980s). During the post-euro period the price of inflation risk is large and positive in the first three years, while the price becomes negative in 2002 and 2003. Overall, these findings suggest that even when nominal exchange rate fluctuations are not present, differences in inflation rates across countries may lead to non-zero risk premia. This may have important consequences asset managers and corporate finance practitioners.

4.7 Conclusions

This chapter analyzes whether inflation risk is priced in international asset returns. We test two assumptions commonly made in the international asset pricing literature. First, the Solnik-Sercu version of the ICAPM as well as the empirical tests of the ICAPM by Dumas and Solnik (1995) and De Santis and Gérard (1998) assume that domestic inflation rates expressed in local currency are non-stochastic and hence inflation risk is not priced. An empirical analysis of the specification of the ICAPM with *real* exchange rate risk presented in this chapter provides an assessment of the validity of this assumption. Second, the ICAPM does not allow for a specification in which inflation risk and nominal exchange rate risk are treated as separate sources of risk. Although inflation risk is often hinted at as an important risk factor, we are not aware of any theoretical or empirical research that studies this distinct source of risk in the context of an international asset-pricing model. Finally, the finding that inflation risk is priced would have important consequences in light of the establishment of the EMU in 1999. While nominal exchange rate fluctuations within the euro area have been brought to an end in 1999, differences in inflation rates between European countries may involve nontrivial inflation risk.

Using the methodology of De Santis and Gérard (1997, 1998), we estimate and test our model including inflation risk factors using asset returns from Germany, France, Japan, the U.K., and the U.S. over the period 1975-1998. We find strong evidence in favor of the hypothesis that inflation risk is priced in international security returns. Inflation risk prices are highly significant, both jointly and for all four individual countries in the sample vis-à-vis Germany. The prices of inflation risk vary considerably over time and the hypothesis that the price of inflation risk is constant is rejected at any conventional significance level. Our findings indicate that the world price of market risk as well as the world prices of nominal exchange rate risk are also highly statistically significant. As the prices of inflation and nominal exchange rate risk are significantly different, we find evidence against the restrictive specification of the ICAPM. It is interesting to note that in the ICAPM with *real* exchange rate risk, only the world market portfolio and the real exchange rates of Japan and the U.K. bear a significant price of risk. The real exchange rates of France and the U.S. are not priced. Given the fact that we do find significant prices for both nominal exchange rate risk and inflation risk for France and the U.S., this result can at least partly be explained by offsetting premia for these sources of risk.

Inflation risk factors also have an economically important impact on expected asset returns. The average contribution of the aggregate inflation risk premium in equity returns (in absolute value) ranges from 26 basis points per month for Germany to more than 56 basis points for France. During some periods (notable the early 1980s) aggregate inflation risk premia assumed values that were considerably higher. Moreover, these aggregates neglect offsetting effects in the risk premia related to the inflation differentials between individual countries. For instance, even the inflation risk associated with inflation differentials between the closely integrated economies of France and Germany is substantial. The mean absolute value of this risk premium amounts to 12 (35) basis points per month in German (French) equity returns over the period 1975-1998. The magnitude of inflation risk premia is generally of the same order as nominal exchange rate risk premia.

Finally, we examine the importance of EMU inflation risk after the introduction of the euro by extending our analysis to the period 1975-2003. We show that inflation risk related to French-German inflation differential still has a considerable effect on expected security returns after 1999. Our results have important implication for portfolio management and capital budgeting.

4.A. Empirical methodology for section 4.6 The termination of nominal exchange rate risk in the euro area

This appendix contains a detailed description of the methodology used to estimate the conditional model in section 4.6. Because this analysis covers both the pre-euro and the post-euro period and we include both Germany and France, our estimation procedure has to take into account that the nominal exchange rate between these countries has been frozen after they adopted the euro. This implies a structural break in the nominal exchange rate series, as a result of which we cannot use the same specification for this risk factor before and after 1999. In general, the structural break leads to two versions of equation (4.3):

$$\begin{aligned} E[r_{it} \mid \Omega_{t-1}] &= \delta_{m,t-1} \operatorname{cov}[r_{it}, r_{mt} \mid \Omega_{t-1}] + \sum_{l=1}^{L} \delta_{l,t-1} \operatorname{cov}[r_{it}, s_{lt} \mid \Omega_{t-1}] \\ &+ \sum_{l=1}^{L} \gamma_{l,t-1} \operatorname{cov}[r_{it}, (\pi_{lt} - \pi_{0t}) \mid \Omega_{t-1}] \qquad i = 1,\ldots,M \qquad t < Jan\ 1999 \end{aligned} \tag{4.13}$$

Equation (4.13) is exactly the same as equation (4.3) and holds as long as the nominal exchange rates are not frozen (the euro was adopted on January 1, 1999). Suppose, without loss of generality, that the euro area exchange rates are the last N excess returns in r_{it}, then as the model for the second part of the sample period can be expressed as follows:

$$\begin{aligned} E[r'_{it} \mid \Omega_{t-1}] &= \delta_{m,t-1} \operatorname{cov}[r'_{it}, r_{mt} \mid \Omega_{t-1}] + \sum_{l=1}^{L-N} \delta_{l,t-1} \operatorname{cov}[r'_{it}, s_{lt} \mid \Omega_{t-1}] \\ &+ \sum_{l=1}^{L} \gamma_{l,t-1} \operatorname{cov}[r'_{it}, (\pi_{lt} - \pi_{0t}) \mid \Omega_{t-1}] \qquad i = 1,\ldots,M-N \qquad t \geq Jan\ 1999 \end{aligned} \tag{4.14}$$

where N is the number of frozen nominal exchange rates and r'_{it} denotes the vector of $(M - N)$ excess returns. In our empirical application, all parameters in the mean equation of (4.14) are estimated using the full sample period, while the parameters concerning the frozen exchange rates are based on data until December 1998 only.

The structural break also has consequences for the estimation of the conditional covariance matrix. Because the number of elements in the return vector decreases as of January 1999, the size of covariance matrix is reduced. This means that after 1999 we only use the upper $(M - N) \times (M - N)$ part of the original covariance matrix. The same holds for the parameters, as only the first $(M - N)$ values of the vectors a and b apply after 1999. The new covariance matrix equation is as follows (with new notation for all symbols to denote the difference with equation (4.7)):

$$
\begin{aligned}
H'_t = H'_0 * (\iota\iota' - cc' - dd') + cc' * \eta_{t-1}\eta'_{t-1} + dd' * H'_{t-1} \\
c = a[1 : M - N] \\
d = b[1 : M - N] \\
\eta_{t-1} = \varepsilon_{t-1}[1 : M - N]
\end{aligned}
\qquad \textbf{(4.15)}
$$

where H'_t is the $(M - N) \times (M - N)$ covariance matrix at time t and H'_0 is the $(M - N) \times (M - N)$ unconditional covariance matrix. The unconditional covariance matrix H'_0 is set equal to the sample covariance matrix of the returns over the full sample, while the H_0 of equation (4.7) is based on the sample until December 1998. This is necessary in order to provide a plausible estimate of the covariances with the nominal exchange rates that disappear after January 1999. Naturally, this leads to a discrepancy between the two covariance matrices and thus our results in the application should be interpreted with care.

Part II

Integration and Contagion in the European Banking Sector

Chapter 5

Financial Integration Through Benchmarks: The Case of the Banking Sector

5.1 Introduction

The motivation of this chapter is a compelling paradox in the banking sector in the European Union (EU). Over the last decades the EU pursued the creation of a single banking market as a cornerstone for a single market for services. Starting with the First Banking Directive[48] in 1977, the banking regulations have been harmonized to a high degree within the European Union. In 1985 the White Paper on "Completing the Internal Market" by the European Commission, establishing free circulation of goods, people, and capital, created the pathway for a single banking market. The paradox is that despite all these changes most of the banks are still very domestically orientated. For example, a recent article in the Financial Times says the following as a reaction to the bid by Spain's Santander Central Hispano for Britain's Abbey National:

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[48] Directive 77/780/EEC on *The Coordination of Laws, Regulations and Administrative Provisions Relating to the Taking Up and Pursuit of Credit Institutions.*

> "*The main reaction, however, has been to see the bid ... as an exception that proves the rule that European retail banking is still overwhelmingly conducted along national lines*".[49]

There is a vast literature on banking and banking regulations. For example, Dermine (2003) presents an overview of European banking, covering both the past and the future developments of this industry. He covers in detail the harmonization process, the consequences of the integration process in the EU and the introduction of the common currency for the banking industry in Europe. The present EU banking sector forms a single banking market, with home country control and mutual recognition. By law, any provider of banking services can establish itself across the Union and is entitled to the same rights as all existing banks in that country. From 1990-2000 the number of mergers and acquisitions has increased in the EU (Slager, 2004), which might be partly contributed to the changes in the regulatory system. However, the banking industry in the EU remains fragmented in practice, since most acquisitions are domestic. The banks that venture a foreign investment through branches, joint ventures or acquisitions, do not attain high market shares in other European countries. Possible reasons for this fact are issues of trust, asymmetric information and transaction costs. A closely related study by Gual (2004) provides similar conclusions. Although the harmonization process has progressed substantially, there are a couple of reasons why the integration process is not complete. The main reasons are natural or strategic barriers (like distance and language) and other important differences (company law, contract law and fiscal matters).[50]

In this chapter we take a different point of view and evaluate integration of banks' stock returns across the European Union. We extend the methodology of De Nicoló and Kwast (2002), who examine the relation of systemic risk with financial consolidation by measuring an increase in bivariate correlations, by not only estimating the level of bank

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[49] The Financial Times Limited, 2004, "Borderless Banking: Why are pan-European Financial Mergers so hard?", *Financial Times* (London, England), 9 September 2004.

[50] To a certain extent, the situation in the European Union is comparable to the US banking industry. Until the end of the 1970s the US had a very segmented banking sector, since the states limited geographical expansion by blocking the entry of banks from other states. After that period states slowly started relaxing these laws, paving the way for a more national banking system. By now, the US banking sector has become highly integrated and the percentage of US banks' assets held by out-of-state bank holding companies is high (in only a few states this percentage is lower than 40%, see Morgan, Rime and Strahan 2003). Here lies the most important difference between the US and European banking sector. Although banking regulations have been harmonized over the last decades, the actual integration of the banking sector is far less developed in Europe than in the US. This can, e.g., be seen from the low market share of foreign banks in the EU (in 1999, this percentage is in most EU-countries lower than 10%). According to Slager (2004), who studies internationalization of major global banks from 1980-2000, argues that European integration cannot be compared to the U.S. banking deregulation. This is due to the fact that it is hard to exploit potential efficiency gains and that fiscal policies on savings and pensions are not harmonized.

equity integration but also simultaneously find an estimate for a separate proxy of the systemic risk potential, which is purely based on risky periods. As a result, we argue that our estimate for the systemic risk potential is more accurate than using the stock price correlations directly as De Nicoló and Kwast (2002)[51]. Our argument is supported by other papers[52] showing that correlations during more volatile (bear) markets are higher than usual.[53] Given these considerations, we estimated a regime-switching model to differentiate between the states that bank returns can be in. Such a model is capable to incorporate the behavior of banks' asset return in different states of the world. Furthermore, Ang and Bekaert (2002) show that a regime-switching specification can deal with changing correlations during volatile (bear) markets.

Our main finding is that, contrary to the lack of *real* integration, we do find an increase in the level of equity market integration for big European banks, while the stock returns of smaller banks show a more diverging behavior. Simultaneously, we find that the (systemic) risk, as measured by the correlation in the high volatility regime, has not increased for most bank pairs in our sample. We argue that a likely explanation for this result is caused by the changes in the demand for European stocks. Institutional investors have increased their holdings in European stocks as a result of both the common currency and the relaxation of restrictive rules on their foreign equity position. As a result of both these issues institutional investors have changed their investment styles in European stocks towards a more sector-oriented approach. Consequently, the banks with the higher market capitalizations will likely be included in the benchmark portfolios of these investors. As a result the stock prices of the larger banks will become more correlated. A possible implication of our finding is that banks may follow different strategies. One strategy is to remain small and target the activities to specific segments (specialization). Another strategy is to become a larger bank that offers a wide range of services. As a result the latter bank will likely be part of the benchmark index for the European banking sector. The advantages for these banks are obvious: better access to capital providers, lower costs of capital and higher credit ratings.

The rest of this chapter is organized as follows. In the next section we will discuss the methodology in more detail. In section 5.3 a description of the data that we use in this chapter is given. The results will be discussed in section 5.4 and section 5.5 concludes.

[51] See De Bandt and Hartmann (2001) for a detailed overview of research on systemic risk.
[52] See e.g. Campbell, Koedijk and Kofman (2001), Longin and Solnik (2001) and Forbes and Rigobon (2002)
[53] A related area of research centers on the high volatility periods specifically and studies the possibility of contagion. See e.g., Gropp and Moerman (2004) who study contagion for the European banking sector using a non-parametric approach.

5.2 Methodology

This section describes the models that we apply in this chapter. As discussed in the introduction we are interested in the level of the interdependencies between stock prices of European banks and especially the change in its level. We model these interdependencies with a conditional correlation structure. A regime-switch model governs the dynamics in the correlation structure. In this study we will concentrate on a regime-switch model with time varying correlations, which is an extension to the model proposed by Ang and Bekaert (2002).[54]

A well-known characteristic of stock returns is that they do not follow a normal distribution. In particular, when considering the joint behavior of stock returns, there is evidence that the behavior of the returns in the tails is different from the non-tail returns. Historical returns show that large negative shocks tend to spill over to other markets easier than regular shocks.[55] The correlation or interdependence between stock markets seems to be higher in the (negative) tail of this distribution than the correlation of the whole distribution. This phenomenon has led to a stream of literature, which tries to estimate the changes in the correlations after a large shock. See, for example, Boyer et al. (1999), Longin and Solnik (2001), Forbes and Rigobon (2002), and Corsetti et al., (2002). One of the conclusions is that the estimated conditional correlation is biased upwards as soon as the volatility increases. Several adjustments have been proposed, but there is still no consensus or method to estimate the coefficients in an unbiased manner. However, it is clear that we need to correct for this bias, because Longin and Solnik (2001) show using exceedence correlations that the normal distribution (with or without GARCH-adjustments) is not capable at all to reconstruct the same exceedence correlations from the data. Ang and Bekaert (2002) show that a multiple regime-switch model is capable in explaining the exceedence correlations much better than earlier proposed models by, for example, Longin and Solnik (2001). The performance improvement can be explained by the fact that a regime-switch model is much more flexible in terms of modeling the persistence in both the conditional means and variances, compared to the single-regime bivariate approach in Longin and Solnik (2001).

Our model is based upon bivariate comparisons between bank equity returns. Let R_{it} and R_{jt} be the local returns on bank i and j, respectively. Let R_{Mt} be the return on a broad European stock index, like the STOXX index.[56] Let $e_{ij,t+1}$ be the exchange rate return

[54] Baele, Vander Vennet and Van Landschoot (2004) also use a regime-switch model in order to investigate whether stock returns of banks with different risk profiles exhibit different risk sensitivities over the business cycle. They find that better capitalized and functionally diversified banks are better protected against business cycle troughs.
[55] This idea was also pursued in the articles by Longin and Solnik (2001) and Forbes and Rigobon (2002), although they used a different modeling approach.
[56] See Section 3 for a description of the data.

between the currencies in which bank *i* and *j* returns are denominated. If these currencies are the same, the exchange return is equal to zero. In the case of two banks from the euro area, the exchange rate factor is equal to zero as of 1 January 1999. We assume that the individual returns have one common factor: the market return. The bivariate model is based upon the following equation:

$$\begin{bmatrix} R_{i,t+1} \\ R_{j,t+1} \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} + \begin{bmatrix} \beta_i \\ \beta_j \end{bmatrix} R_{M,t+1} + \begin{bmatrix} \gamma_i \\ \gamma_j \end{bmatrix} e_{ij,t+1} + \Sigma_t^{1/2}(s_{t+1}) \begin{bmatrix} \varepsilon_{i,t+1} \\ \varepsilon_{j,t+1} \end{bmatrix} \quad \textbf{(5.1)}$$

We assume that the $\varepsilon_{i,t+1}$ ($\varepsilon_{j,t+1}$) are identically and independently normally distributed with variances equal to 1, and $\Sigma_t(s_{t+1})$ is the covariance matrix of the returns. Note that we do not allow the 2x1 coefficient vector of means (α_i, α_j)' to vary between regimes.[57] This is motivated by the results in Ang and Bekaert (2002) who show that the hypothesis of equal estimates of the conditional means (α_i, α_j)' in different regimes cannot be rejected. By not making these coefficients state-dependent, the parameter estimate is much more robust. Estimation of the more general regime-switch model does not change our general findings.[58]

The regimes s_{t+1} follow a Markov chain with constant transition probabilities. We assume that the individual variances of the two stock returns can be in either a high or a low regime. This implies that we have 4 (2 x 2) regimes, which can be written as:

$$\Sigma(s_{t+1}) = \begin{cases} \begin{pmatrix} \sigma_{i,low}^2 & \rho_1 \sigma_{i,low}\sigma_{j,low} \\ \rho_1 \sigma_{i,low}\sigma_{j,low} & \sigma_{j,low}^2 \end{pmatrix}, \text{if } s_{t+1} = 1, \\ \begin{pmatrix} \sigma_{i,low}^2 & \rho_2 \sigma_{i,low}\sigma_{j,high} \\ \rho_2 \sigma_{i,low}\sigma_{j,high} & \sigma_{j,high}^2 \end{pmatrix}, \text{if } s_{t+1} = 2, \\ \begin{pmatrix} \sigma_{i,high}^2 & \rho_3 \sigma_{i,high}\sigma_{j,low} \\ \rho_3 \sigma_{i,high}\sigma_{j,low} & \sigma_{j,low}^2 \end{pmatrix}, \text{if } s_{t+1} = 3, \\ \begin{pmatrix} \sigma_{i,high}^2 & \rho_4 \sigma_{i,high}\sigma_{j,high} \\ \rho_4 \sigma_{i,high}\sigma_{j,high} & \sigma_{j,high}^2 \end{pmatrix}, \text{if } s_{t+1} = 4. \end{cases} \quad \textbf{(5.2)}$$

In words, we allow for a covariance structure of the two stock returns that can vary between either low or high states. In order to restrict the number of parameters we structure the transition matrix in the following way:

$$\Pi = P \otimes Q \quad \textbf{(5.3)}$$

[57] Likewise, we do not allow for regime-dependent vectors $(\beta_i, \beta_j)'$ and $(\gamma_i, \gamma_j)'$.

[58] These results are available from the authors upon request.

with P and Q transition matrices.

$$P = \begin{pmatrix} p_{i1} & 1-p_{i2} \\ 1-p_{i1} & p_{i2} \end{pmatrix} \quad \textbf{(5.4)}$$

$$Q = \begin{pmatrix} q_{j1} & 1-q_{j2} \\ 1-q_{j1} & q_{j2} \end{pmatrix} \quad \textbf{(5.5)}$$

where $p_{i1} = \Pr\left[s^i_{t+1} = low \mid s^i_t = low\right]$, is the probability that stock i's volatility remains in the low volatility state. Consequently, $1 - p_{i1} = \Pr\left[s^i_{t+1} = high \mid s^i_t = low\right]$. Likewise, $p_{i2} = \Pr\left[s^i_{t+1} = high \mid s^i_t = high\right]$, and $1 - p_{i2} = \Pr\left[s^i_{t+1} = low \mid s^i_t = high\right]$. This parameterization creates two times two independent regimes, in other words, each asset can be in the low volatility or high volatility regime independent of the state the other asset is in. As a result we have 4 probability parameters governing the transition between regimes.

To complement our model we allow for conditional heteroskedasticity in the returns by imposing an ARCH(1) process on the errors in both the high and low states:[59]

$$\varepsilon_{i,t+1} \mid h_{i,t+1}(low) \sim N\left(0, h_{i,t+1}(low)\right), \textit{ with } h_{i,t+1}(low) = \omega_{i,low} + \delta_{i,low}\varepsilon^2_{i,t+1} \quad \textbf{(5.6)}$$

$$\varepsilon_{i,t+1} \mid h_{i,t+1}(high) \sim N\left(0, h_{i,t+1}(high)\right), \textit{ with } h_{i,t+1}(high) = \omega_{i,high} + \delta_{i,high}\varepsilon^2_{i,t+1} \quad \textbf{(5.7)}$$

Note that this model nests the constant volatility model. When the coefficients $\delta_{i,low}$ and $\delta_{i,high}$ (i, j=1,2) are zero, we have a constant volatility model again.

We are mainly interested in the interdependence structure of European banks over time. With the regime-switch specification we can distinguish between a higher rate of integration and a 'higher risk of contagion'. In this chapter integration and contagion are defined from a pure statistical point of view by focusing on the correlation coefficient. More specifically, regime 1 measures the interdependence between the banks in "normal" (low volatility) markets. We expect that the correlation between the European banks' stock returns has risen over the last decade facilitated by the liberalization of European capital markets, the harmonization of monetary and policy rules and the Basel committee requirements, which require banks to have a sound capital structure. We measure this

[59] One could also apply the more familiar GARCH model for describing the conditional heteroskedasticity in each regime (see Gray, 1996), however, the regime switch specification already subsumes a lot of the heteroskedasticity of the asset returns. Furthermore, Kim and Nelson (1999) argue that modeling GARCH in the regime switch specification would destroy the Markov properties of the process through the lagged conditional variance measure.

hypothesized increase in the correlation coefficient by allowing for a linear time trend in the correlation. That is, we replace the coefficients ρ_i (i=1,…,4) in (2) with:

$$\rho_{t+1}(s_{t+1}) = \overline{\rho}(s_{t+1}) + \lambda_1 \times (t+1), \qquad s_{t+1} = 1,\ldots,4, \tag{5.8}$$

with λ_1 a parameter that applies to all regimes and the $\overline{\rho}(s_{t+1})$ regime-dependent constant parameters. Formulating the time-behavior of the correlations in this way, we are able to test for a higher rate of integration between banks by investigating the significance of λ_1. The functional specification of the correlation coefficient forces it to lie between –1 and 1.[60]

Furthermore, we want to investigate the level of interdependence during times of financial distress and especially whether this changes over time. Motivated by Longin and Solnik (2001) we enrich the correlation dynamics in the high volatility regime (s_{t+1} = 4) by adding another time trend:

$$\rho_{t+1}(4) = \overline{\rho}(4) + (\lambda_1 + \lambda_2) \times (t+1). \tag{5.9}$$

This specification allows us to test whether in a joint high-volatility regime the correlation trend differs from those in other regimes. In other words, this formulation allows us to test whether the risks during volatile (bear) markets has increased more than proportionally. A positive value for λ_2 would signify an increased risk during volatile markets, while a negative value indicates that asset returns are more spread during periods of high volatility. The outcome can be an important input in the discussion about the efficiency of the Basel agreements.

5.3 Data

We will use stock data from the largest banks in Europe from the DataStream database. Our data period covers the period from 1 January 1990 to 3 March 2003. The data is sampled at a weekly frequency, which results in 687 weekly observations. Ideally we would like to use stock data from the largest European commercial banks. Unfortunately, not for all these banks data is available for the complete data period. An important reason for this is that many banks have merged or have been acquired by other banks as a result of the consolidation process in the European banking sector (see Slager, 2004). We opted for a balanced sample, thereby deleting banks that do not have stock price data available for

[60] In order to force the correlation coefficients to the interval [-1,1] we use a logistic function in our likelihood evaluations: $\rho_{t+1}(s_{t+1}) = 2\dfrac{\exp(\overline{\rho}(s_{t+1}) + \lambda_1(t+1))}{1+\exp(\overline{\rho}(s_{t+1}) + \lambda_1(t+1))} - 1$.

Table 5.1
Summary Statistics

This table summarizes the statistics of the weekly returns of the 41 European banks in our sample. The lowest row of the table also contains the statistics of the Dow Jones Euro STOXX 600 index that we used to proxy the European market. Sample period: January 1, 1990 – March 3, 2003. The first column of the table presents the market capitalization of the bank (measured in 2000, Bankscope).

	Bank	Market capitalization	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
1	Fortis	332,092	0.166	4.18	-21.19	16.62	-0.311	5.61
2	KBC Bank	176,909	0.205	3.78	-15.25	21.74	0.374	6.48
3	Bayerische Hypo- und Vereinsbank	694,300	0.015	4.89	-19.95	21.67	-0.093	5.86
4	Commerzbank	454,500	-0.029	4.55	-17.70	29.33	0.198	7.70
5	Deutsche bank	927,900	0.076	4.17	-16.54	22.70	0.038	5.30
6	IKB Deutsche Industriebank	32,359	0.039	2.49	-9.06	11.45	0.155	5.29
7	Danske Bank	182,520	0.220	3.49	-12.18	15.69	0.341	4.61
8	Jyske Bank	17,044	0.191	3.22	-21.09	25.81	0.750	13.75
9	Banco Bilbao Vizcaya Argentaria	292,557	0.276	4.77	-19.64	27.96	0.378	7.41
10	Banco Espanol de Credito	44,381	0.017	5.72	-61.95	65.65	0.694	49.49
11	Banco Popular Espanol	31,288	0.325	3.77	-16.38	14.33	0.138	4.36
12	Banco Santander Central Hispano	347,288	0.249	4.85	-24.34	22.60	-0.141	5.93
13	Natexis Banques Populaires	113,131	0.069	4.15	-16.81	18.35	0.269	5.10
14	Societe Generale	455,881	0.266	5.16	-22.08	26.85	0.274	5.50
15	Alpha Bank	30,183	0.476	5.99	-21.59	29.28	0.701	6.15
16	Commercial Bank of Greece	16,164	0.528	7.54	-34.06	57.66	1.247	10.86
17	EFG Eurobank Ergasias	16,833	0.482	7.92	-29.25	46.90	1.850	12.18
18	Allied Irish Banks	77,932	0.284	4.12	-15.45	16.58	-0.063	4.69
19	Anglo Irish Bankcorp	11,047	0.383	4.39	-13.25	17.50	0.354	4.28
20	Bank of Ireland	73,859	0.372	4.07	-17.06	13.23	-0.007	3.93
21	Banca Agricola Mantovana	10,190	0.140	2.98	-14.43	21.36	0.756	11.60
22	Banca Intesa	331,364	0.267	5.69	-22.05	38.55	0.930	8.99
23	Banca di Roma	132,729	-0.017	6.09	-22.82	35.89	0.739	7.89
24	Banca Populare Bergamo	37,670	0.141	3.38	-12.20	16.84	0.475	5.73
25	Banca Populare Commercial e Industria	20,911	0.066	3.95	-16.83	31.39	1.031	12.63
26	Banca Populare di Intra	3,929	0.195	3.39	-13.15	15.82	0.595	6.22
27	Banca Populare di Lodi	34,223	0.083	3.90	-15.31	24.22	0.583	7.55
28	Banca Populare di Milano	28,282	0.094	4.70	-29.58	24.62	0.302	7.17
29	Credito Emiliano	15,148	0.135	5.89	-18.83	27.60	0.751	5.48
30	Credito Valtellinese	7,416	0.074	2.93	-17.39	13.94	0.651	9.04
31	Unicredito Italiano	202,649	0.294	5.65	-26.49	53.70	1.619	16.54
32	Banco Comercial Portugues	61,850	0.043	3.72	-14.36	25.00	0.980	10.21
33	Skandinaviska Enskilda Banken (SEB)	118,261	0.363	8.23	-47.54	120.90	5.101	75.33
34	Svenska Handelsbanken (SHB)	114,194	0.378	5.79	-22.54	69.30	3.239	39.25
35	Abbey National	293,395	0.212	4.41	-15.54	21.30	0.199	4.96
36	Barclays	486,936	0.294	4.69	-17.77	22.49	0.162	5.07
37	Close Brothers	3,241	0.301	4.54	-17.74	30.92	0.482	8.38
38	Schroders	4,180	0.278	4.73	-24.56	24.58	-0.163	7.31
39	Singer & Friendlander Group	2,792	0.180	4.32	-14.16	25.10	0.839	6.25
40	Standard Chartered	161,964	0.392	5.58	-22.43	42.31	0.728	8.69
41	Royal Bank of Scotland	206,176	0.413	4.91	-21.10	21.70	0.185	5.62
	Dow Jones Euro STOXX 600 index		0.157	2.44	-12.49	7.30	-0.597	5.49

the whole sample. The number of remaining banks is equal to 41. We recognize that this procedure could cause our results to suffer from selection bias. Caution should be kept when interpreting the results in the sense that our results apply to the chosen banks only. In Table 5.1 we list the banks in our sample together with some descriptive statistics. We leave the problem of including banks with shorter sample periods in our analysis for further research.

Since we have banks' stock returns from countries with different currencies we need to consider the impact of the relevant exchange rates. As our methodology focuses on the joint dynamics of bank shares we chose to use returns denoted in local currencies. In order to allow for a possible impact of exchange rates we have included an exchange rate factor in equation (5.1) for bank pairs shares denoted in different currencies. The weekly exchange rates are taken from DataStream.

The market return that we use is the Dow Jones Euro STOXX 600 index, which is a broad index on European stocks denoted in euros.[61] In Table 5.1 we have included the summary statistics for this series as well.

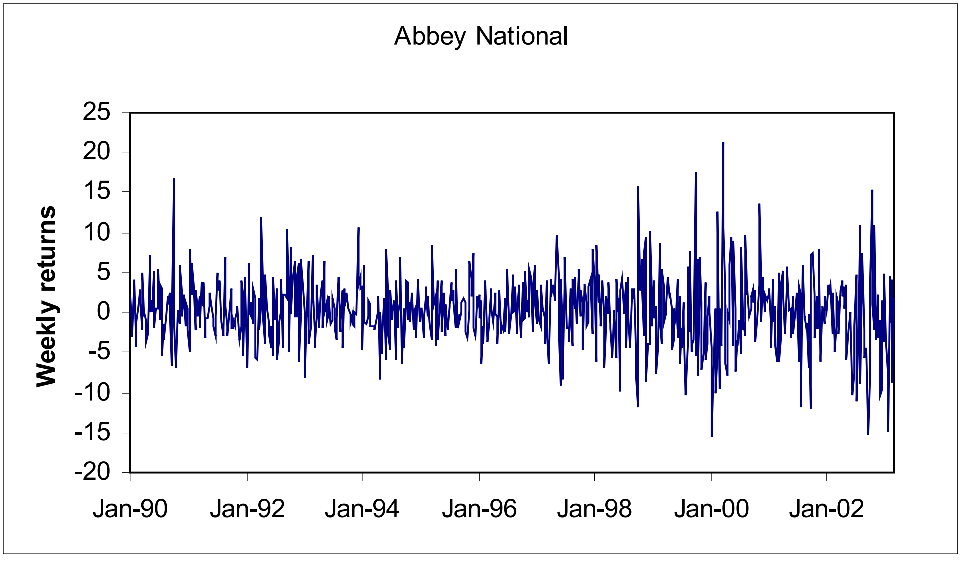
5.4 Results

Using the returns on bank shares we apply the model suggested in section 5.2 on each combination of banks. In order to have an impression of the estimation results for one particular combination of banks we present the estimation results of the regime switch model for Bayerische Hypo- und Vereinsbank (BHVB) from Germany and Abbey National from the U.K. The range of products that these banks offer is relatively similar (mortgages). The local currency denominated stock returns for both banks are plotted in Figure 5.1. In Table 5.2 we have listed the estimation results from the regime switch model. All parameters in the mean equation (5.1) are significant. The variance parameters σ_i (i=1,…,4) show that the regimes are in line with the model set-up. Based on a likelihood ratio selection criterion we add conditional variance terms - through an ARCH model, see equations (5.6) and (5.7) - to the model in regimes 1 and 2.[62] The constant terms in the correlation specifications (equation (5.8)), and the special case for the high volatility regime (equation (5.9)), show that the constant correlation coefficients $\overline{\rho}_i$ (i=1,…,4) between returns is negative except for regime 2. More interestingly, we see that λ_1 is negative, albeit not significantly, implying that there is a tendency for the correlation coefficient between these two banks to decline over time. The high volatility

[61] STOXX, STOXX Limited, http://www.stoxx.com (accessed June 03, 2003).
[62] Estimation results from this procedure can be obtained from the authors.

Figure 5.1
Returns on Bayerische Hypo- und Vereinsbank and Abbey National

We consider one specific bank pair in more detail: Bayerische Hypo- und Vereinsbank and Abbey National. This figure depicts the weekly return series of both assets, which served as an input to the regime-switching model. The upper graph is the picture of the returns of the German bank and the lower graph depicts the returns of Abbey National.



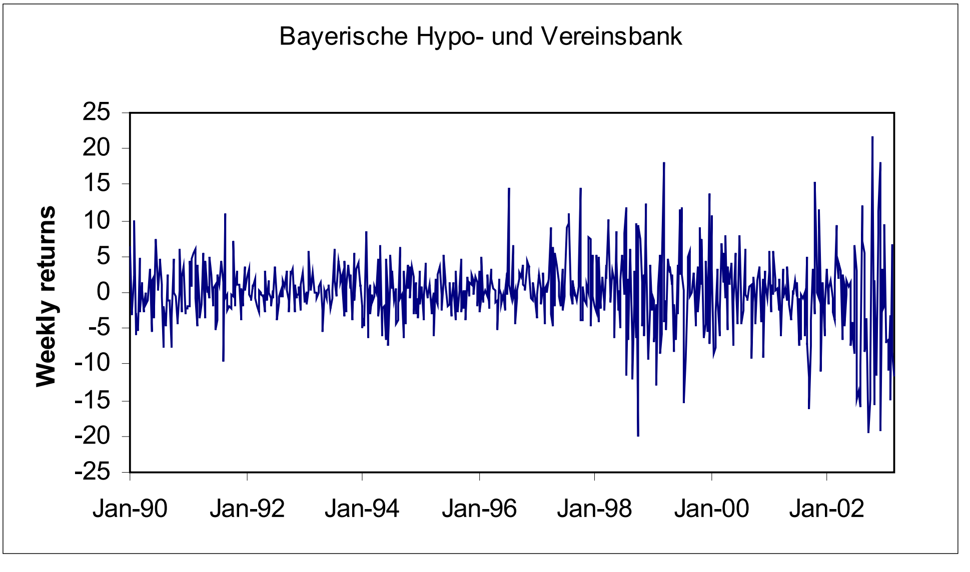


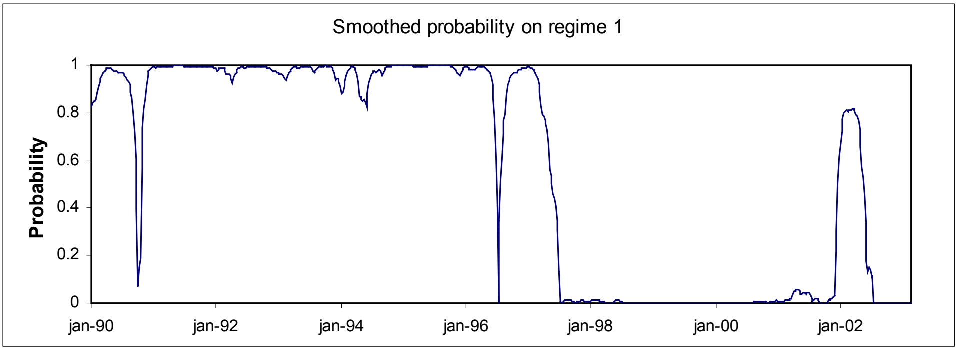
Table 5.2
Estimation results of the regime switch model:
Bayerische Hypo- und Vereinsbank and Abbey National

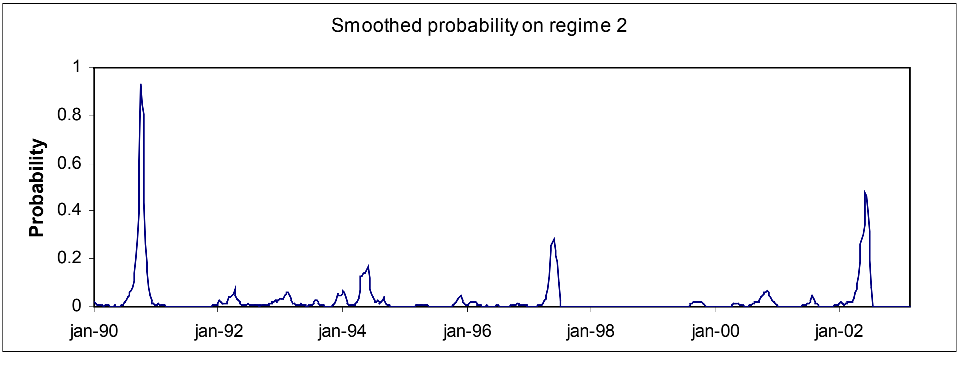
This table presents the parameter estimates and standard errors of the complete regime switching model for one specific bank pair: Bayerische Hypo- und Vereinsbank (denoted by bank1) and Abbey National (denoted by bank2). The four states in the variance equation are based on the two possible states that each banks asset can be in. State 1(4) represents the state where both assets' volatilities are low(high), while state 2 is the state where the volatility of bank 1 is low, while the volatility of bank 2 is high, for state 3 the other way around.

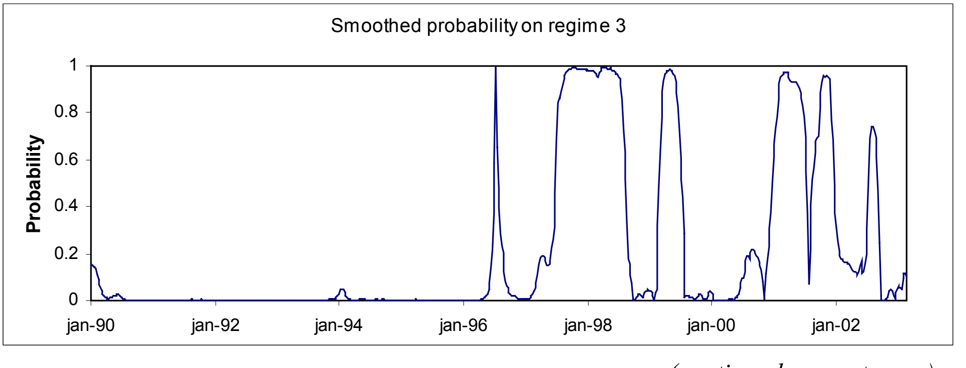
	Parameter estimates		Standard error
Mean equation			
α_1 Constant, bank1	-0.081	***	0.013
α_2 Constant, bank2	0.146	***	0.016
β_1 Market, bank1	1.079	***	0.004
β_2 Market, bank2	0.944	***	0.004
γ_1 Exch.rate, bank1	0.310	***	0.010
γ_2 Exch rate, bank2	0.504	***	0.012
Variance equation			
$\omega_{1,\text{ low}}$	5.63	***	0.298
$\omega_{1,\text{high}}$	22.28	***	8.540
$\omega_{2,\text{low}}$	8.48	***	0.530
$\omega_{2,\text{high}}$	35.70		29.56
$\delta_{1,\text{low}}$	0.034	***	0.004
$\delta_{1,\text{high}}$	0.307	***	0.010
$\delta_{2,\text{low}}$	0		--
$\delta_{2,\text{high}}$	0		--
$\bar{\rho}_1$	-0.060		0.031
$\bar{\rho}_2$	0.452		0.471
$\bar{\rho}_3$	-0.017		0.144
$\bar{\rho}_4$	-0.518		1.661
Transition parameters			
P_{11}	0.992	***	0.000
P_{22}	0.991	***	0.000
Q_{11}	0.986	***	0.000
Q_{22}	0.953	***	0.000
Lambda parameters			
λ_1	-0.226		0.192
λ_2	1.165		2.847

Figure 5.2
Smoothed probabilities for Bayerische Hypo- und Vereinsbank versus Abbey National

This is an example of the smoothed probabilities of our regime-switching model. The pictures below show the smoothed probabilities of all four possible states for the complete bank pair model (i.e. including the parameters λ_1 and λ_2) for the bank pair: Bayerische Hypo- und Vereinsbank and Abbey National.







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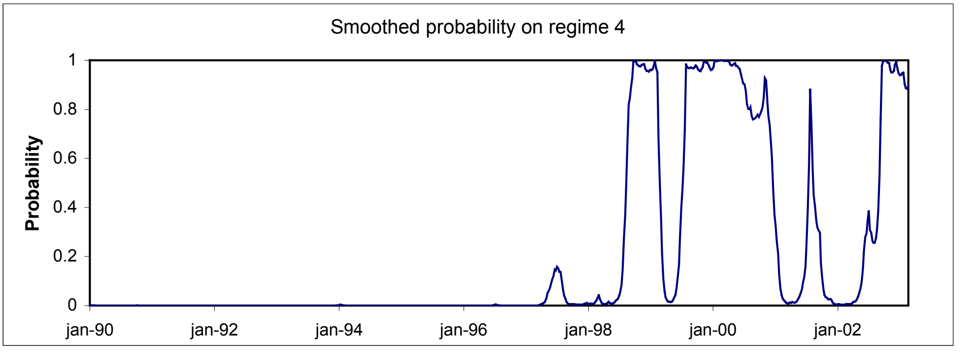


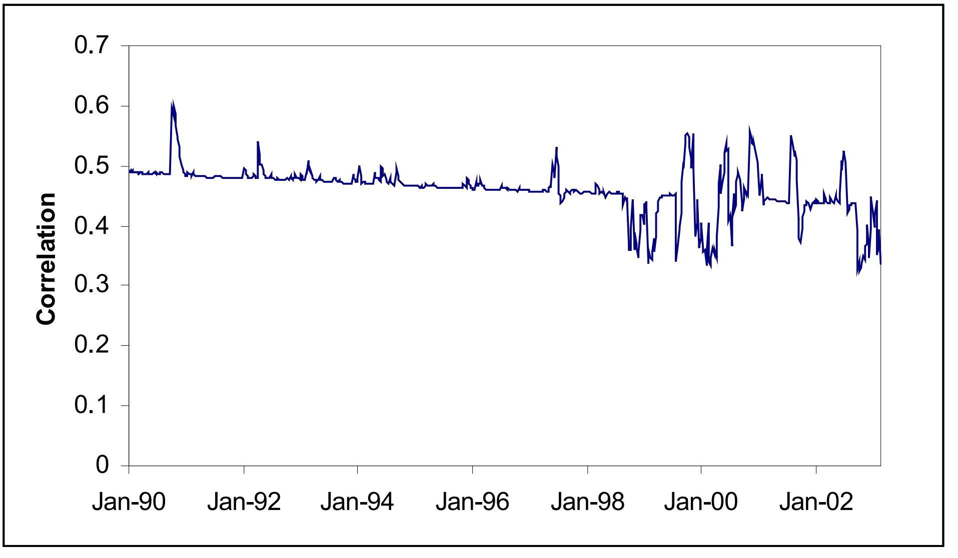
regime correlation correction parameter λ_2 is positive (again not significantly so), suggesting that the returns between these banks are increasingly higher correlated in that regime.

In order to obtain an idea about the impact of the parameter values in each of the regimes we need to find out what regime is the most likely at every moment in the sample period for the bivariate return process. This can be achieved by calculating the smoothed regime probabilities that we present in Figure 5.2.[63] In the first half of the sample regime 1 is the most dominant one. Later, starting around 1997, regimes 3 and 4 are the most dominant ones. Regime 2 (high volatility for Abbey National and a low volatility for BHVB) does not occur frequently. Together with the previous observation this implies that the volatility of BHVB in general is higher than the volatility of Abbey National. The fact that regime 1 cannot be found in the latter part of the sample suggests that the volatility of both return series has increased. As regimes 3 and 4 seem to be the most influential in this period it can be said that the correlation coefficients exhibit some interesting behavior. When both volatilities are high (regime 4) the correlation seems to increase as $\lambda_1 + \lambda_2$ is larger than zero, while the correlation in regime 3 decreases over time (since λ_1 is negative). This can be best seen from Figure 5.3, where the weighted average of the correlation coefficient is depicted.[64]

[63] For background information on calculating smoothed probabilities from a switching regime model see, for example, Kim and Nelson (1999).
[64] Note however that the correlation dynamics are not significant in this example and are mainly used to get an impression of the estimation results.

Figure 5.3
Time varying correlation between BHVB and Abbey National

This graph depicts the changing correlation coefficient over time between the Bayerische Hypo- und Vereinsbank (BHVB) and Abbey National. This coefficient is a weighted average of the four different correlations of each regime, with the weights equal to the inferenced probabilities of the regime-switching model.



In this chapter we are interested in the behavior of the correlation dynamics in the banking sector as a whole. Table 5.3 presents the summary statistics on all the bank pairs that we have investigated[65]. On average the results seem to be in line with the example of BHVB and Abbey National. However, we find that both the λ_1 and λ_2 parameters are (on average) positive, which suggests that the correlation between bank stock returns increases over time, irrespective of the regime. On average the correlation increases faster over time in regime 4. Figure 5.4 plots the λ_1 and λ_2 parameters for all 764 bank pairs. As can be seen from the table already, the dispersion in λ_2 is much higher than in λ_1. Also, the figure suggests that there is a (weak) negative relationship between these two parameters, which would point to an offsetting effect of the two parameters in regime 4, as is the case in our example of BHVB and Abbey National. Note that in general the regimes are identified consistently with the parameter definitions and interpretations from section 5.2.

[65] De Nicoló and Kwast (2002) used the same methodology. They examined the time-varying correlations in a less flexible framework for bivariate US bank returns.

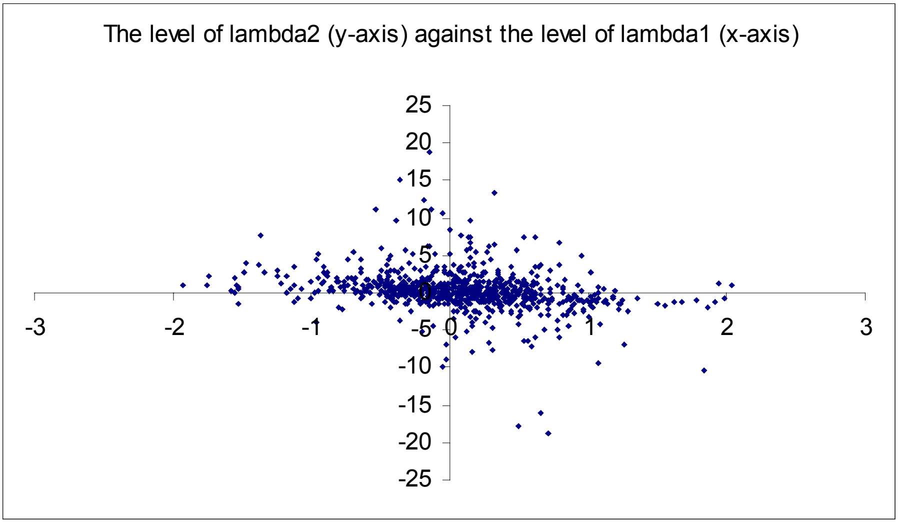
Table 5.3
Statistics of the model coefficients

We have 41 banks in our sample, which would result in 820 bank pairs. For sake of robustness, we excluded some of the models in the following way. 56 of these bank pair models were excluded based on the restriction that all probabilities should be higher than 0.5 and that all correlation coefficients should be smaller than 0.9975 in absolute value. In the deleted pairs the regimes might be too heavily influenced by outliers, which would result in misinterpretations of the regimes. The table below gives the statistics of the model coefficients on the remaining 764 bank pair models. In 434 models a conditional heteroskedasticity correction (ARCH) has been performed.

Parameter	Average	Median	St.dev	Min	Max	Observations
α_1	-0.038	-0.037	0.166	-0.580	0.361	764
α_2	-0.017	-0.028	0.185	-0.538	0.374	764
β_1	0.726	0.733	0.356	0.130	1.404	764
β_2	0.693	0.731	0.356	0.117	1.339	764
γ_1	-0.054	-0.037	0.226	-0.941	0.600	764
γ_2	-0.013	0.000	0.358	-1.071	1.192	764
P_{11}	0.946	0.964	0.052	0.604	0.998	764
P_{22}	0.888	0.934	0.118	0.504	1.000	764
Q_{11}	0.936	0.966	0.072	0.644	0.998	764
Q_{22}	0.878	0.927	0.116	0.502	1.000	764
$\overline{\rho}_1$	0.036	0.012	0.189	-0.401	0.832	764
$\overline{\rho}_2$	0.027	0.022	0.265	-0.945	0.955	764
$\overline{\rho}_3$	0.020	0.008	0.263	-0.968	0.980	764
$\overline{\rho}_4$	0.020	0.034	0.465	-0.989	0.997	764
$\omega_{1,\ low}$	6.06	5.30	4.14	0.70	18.74	764
$\omega_{1,high}$	47.67	23.20	71.87	8.55	651.81	764
$\omega_{2,low}$	7.33	5.94	4.97	0.69	20.36	764
$\omega_{2,high}$	78.04	30.89	146.20	9.67	1,918.45	764
$\delta_{1,low}$	0.113	0.096	0.119	0.000	0.595	434
$\delta_{1,high}$	0.122	0.071	0.134	0.000	0.727	434
$\delta_{2,low}$	0.096	0.096	0.100	0.000	0.603	434
$\delta_{2,high}$	0.117	0.048	0.161	0.000	0.973	434
λ_1	0.076	0.079	0.578	-1.930	2.041	764
λ_2	0.304	0.172	2.845	-18.748	18.700	764

Figure 5.4
Correlation time trend coefficients

This graph depicts the relationship between λ_1 and λ_2. λ_1 is plotted on the horizontal axis and λ_2 is on the vertical axis. The plot shows the λ's of all bank pairs, irrespective of the significance of these parameters.



Based on the set of bivariate estimation results we conduct some analyses on the parameters of interest λ_1 and λ_2 by conditioning on a number of indicators: variance, unconditional correlations, euro membership, and bank sizes. In Table 5.4 we split our sample based on the unconditional variances of the assets under consideration[66]. The upper part of the table concentrates on those bank pairs, where the volatilities of the low states were below (above) the median of $\sigma_{i,low}$ simultaneously. Let's discuss the first row in more detail. It turns out that 188 bank pairs can be identified where $\sigma_{1,low}$ and $\sigma_{2,low}$ are lower than the median of $\sigma_{i,low}$. In 92 of these cases λ_1 is positive, of which 7 are significantly positive. Consequently, in 18 (=25-7) cases λ_1 is significantly negative. In other words, banks that have a relatively low volatility show a decrease in their correlation. On the other

[66] The unconditional variances for each regime can easily be found from the regression results. In case the ARCH components are not significant, the variances of the assets are simply equal to $\omega^2_{i,\text{ state}}$. When an ARCH component is included in the model , the unconditional variance can be calculated using:

$$\sigma^2_{i,state} = \left(\frac{\omega_{i,state}}{1-\delta_{i,low}} \right)^2$$

Table 5.4
Results after a split based on the variance

This table presents some statistics for the parameters λ_1 (time trend in all correlation coefficients) and λ_2 (extra time trend only for regime 4, i.e. when both assets are in the high volatility regime). The whole set of bivariate results is divided into subsets according to a split based on the median of the unconditional variance of each parameter. Based on the subsets we can see whether there are differences for certain classes of assets. The upper part of the table deals with the case of assets that both banks have a lower or higher variance estimate (compared to its median) for the low volatility regime The lower part of the table concentrates on the cases where all four volatilities are lower (higher) than the median of these volatilities. The median of the volatilities is the median over both assets (over $\sigma_{1,low}$ and $\sigma_{2,low}$ for the low volatility, $\sigma_{1,high}$ and $\sigma_{2,high}$ for the high volatility respectively). See footnote 66 for more information on the calculation of the unconditional volatilities. The median unconditional variance of the low and high volatility regime is 5.627 and 29.861 respectively

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
Both volatilities in base regime are simultaneously lower or higher than the median							
λ_1 (variances low in base regime)	188	92	(48.9%)	25	(13.3%)	7	(28.0%)
λ_1 (variances high in base regime)	188	128	(68.1%)	35	(18.6%)	29	(82.9%)
λ_2 (variances low in base regime)	188	100	(53.2%)	19	(10.1%)	9	(47.4%)
λ_2 (variances high in base regime)	188	109	(58.0%)	9	(4.8%)	6	(66.7%)
ALL volatilities are simultaneously lower or higher than the median							
λ_1 (all variances lower)	103	47	(45.6%)	16	(15.5%)	5	(31.3%)
λ_1 (all variances higher)	105	69	(65.7%)	17	(16.2%)	13	(76.5%)
λ_2 (all variances lower)	103	61	(59.2%)	10	(9.7%)	6	(60.0%)
λ_2 (all variances higher)	105	66	(62.9%)	5	(4.8%)	3	(60.0%)

hand, banks that have a relatively high volatility (row 2) seem to become more correlated over time (29 out of 188 cases show a significantly positive estimate for λ_1). We also examine the estimates of λ_2, but these do not show any striking results. The lower part of Table 5.4 summarizes the results in case all four unconditional volatilities are lower or higher than the median for these values. The results confirm the conclusions found in the upper part of the table.

Table 5.5
Results after a split based on the correlation coefficients

This table presents some statistics for the parameters λ_1 (time trend in all correlation coefficients) and λ_2 (extra time trend only for regime 4, i.e. when both assets are in the high volatility regime). The whole subset is divided into subsets based on the estimates of the correlation coefficients. Only the correlations of regime 1 and regime 4 are taken into account, since both assets are then in the same regime (low volatility vs. high volatility).

The first part of the table compares the λ-parameters in case the correlation in regime 1 is lower (higher) than its median (0.012). The second part presents the same for the correlation in regime 4 (median = 0.034). The last part of table takes the intersection of these two restrictions.

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
Subsamples based on the comparison of the *correlation of regime 1* with its median							
λ_1 (corr1 < median(corr1))	382	315	(82.5%)	61	(16.0%)	60	(98.4%)
λ_1 (corr1 => median(corr1))	382	128	(33.5%)	44	(11.5%)	7	(15.9%)
λ_2 (corr1 < median(corr1))	382	164	(42.9%)	24	(6.3%)	7	(29.2%)
λ_2 (corr1 => median(corr1))	382	252	(66.0%)	35	(9.2%)	29	(82.9%)
Subsamples based on the comparison of the *correlation of regime 4* with its median							
λ_1 (corr4 < median(corr4))	382	268	(70.2%)	48	(12.6%)	41	(85.4%)
λ_1 (corr4 => median(corr4))	382	175	(45.8%)	57	(14.9%)	26	(45.6%)
λ_2 (corr4 < median(corr4))	382	322	(84.3%)	34	(8.9%)	34	(100.0%)
λ_2 (corr4 => median(corr4))	382	94	(24.6%)	25	(6.5%)	2	(8.0%)
Subsamples based on the comparison of the *correlation of regime 1 and regime 4* with their medians							
λ_1 (corr1 &corr4 < median)	199	184	(92.5%)	37	(18.6%)	37	(100.0%)
λ_1 (corr1 & corr4 => median)	199	44	(22.1%)	33	(16.6%)	3	(9.1%)
λ_2 (corr1 & corr4 < median)	199	151	(75.9%)	7	(3.5%)	7	(100.0%)
λ_2 (corr1 & corr4 => median)	199	81	(40.7%)	8	(4.0%)	2	(25.0%)

Table 5.6

Differences between euro area countries and non-euro area countries

This table summarizes the statistics on λ_1 and λ_2 based on the country where the banks originate. All bank pair regression thus fall into three separate categories: 1) both banks originate from a euro area country; 2) both banks originate from a country that is not in the European Monetary Union and 3) the two banks come from different subsets, i.e. one is from a euro area country, while the other is not.

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
λ_1 (euro banks only)	413	222	(53.8%)	54	(13.1%)	26	(48.1%)
λ_1 (non-euro banks only)	49	28	(57.1%)	5	(10.2%)	2	(40.0%)
λ_1 (euro vs. non-euro)	302	193	(63.9%)	46	(15.2%)	39	(84.8%)
λ_2 (euro banks only)	413	235	(56.9%)	41	(9.9%)	27	(65.9%)
λ_2 (non-euro banks only)	49	20	(40.8%)	4	(8.2%)	2	(50.0%)
λ_2 (euro vs. non-euro)	302	161	(53.3%)	14	(4.6%)	7	(50.0%)

We perform a similar analysis on a division of the results based on the *level* of the correlation coefficient of regime 1, where both assets are in the low volatility regime, and regime 4, where both assets are in the high volatility regime. The results in Table 5.5 show that the level of the correlation has an impact on the sign and the importance of the time trends in the correlation. These results are not very surprising. Due to the introduction of a time trend for the correlation coefficient, the estimate of the base correlation might differ from the actual average correlation (leverage). The results suggest that the level of the correlation in regime 1 has an impact on the overall time trend (λ_1), while the correlation in regime 4 has a bigger impact on the significance of λ_2. For the observations where the estimate of the correlation of regime 1 (4) is lower than the median, more than 82.5% (84.3%) of the observations has a positive value for λ_1 (λ_2) and 98.4% (100%) of the significant estimates are positive.

Table 5.6 presents the results of conditioning on the fact whether the banks are located in countries, which do or do not use the euro as their main currency. The results indicate that the location does not really matter for the sign of the parameters λ_1 and λ_2.

Again we see that the number of significant correlation parameters is not high (around 10%). We do see, however, that for combinations of banks for which only one bank has a euro home currency, the significant values for λ_1 are predominantly positive.

In Table 5.7 we split our sample in terms of bank size. Based on market capitalizations (measured in 2000, downloaded from the BankScope database) we divide our sample in banks that have market capitalizations that are either higher or lower than the median capitalization (73,859 million euros). The former banks are denoted 'big', the rest is called 'small'. The table shows that estimating the model for two big banks the λ_1 parameter is positive in 142 of the 180 cases (78.9%). Moreover, if the parameter is significant, it is positive in 92.5% of the cases. Interestingly, λ_1 is positive in only 75 of the 191 cases when we estimate the model for *two small banks*, which implies that in 116 cases λ_1 is negative (60.7%). The significant values for λ_1 in this case are predominantly negative (22 out of 27 cases). The results suggest that big European banks are becoming more integrated over time, whereas smaller banks show opposite behavior. This result cannot be attributed to econometrical issues (like conditioning on the base level of the correlation coefficient, see Table 5.5). A reason for this result could be that investors perceive that the activities of bigger banks are becoming more correlated. An alternative explanation can be found in papers by Rouwenhorst (1999), Cavaglia, Brightman, Aked (2000), and Moerman (2004). They argue that (institutional) investors in European capital markets (should) shift from a country-based towards a sector-based approach. As a consequence, investors are tracking industry indices, thereby focusing more on bigger banks than on smaller banks.

The lower half of Table 5.7 reports estimates on the λ_2 parameter. This parameter gives an indication on the level of systemic risk between two bank stocks, since it is measured during highly volatility periods only. In other words, a significantly positive estimate would mean that a portfolio containing these two assets becomes riskier. We find that these risks do not increase over our sample period. For the different groups the number of positive estimates ranges from 52% to 60% and the number of significant estimates is relatively low (less than 10%).

5.5 Conclusions

Although the European banking sector has been deregulated over the last few decades individual banks remain highly focused on their home markets. In this chapter we have analyzed whether this apparent lack of physical or real integration also holds for the stock price behavior of European banks. More specifically, we have analyzed whether the stock price dynamics of individual banks become more correlated.

Based on a sample of stock prices of 41 European banks over the period January 1990 – March 2003 we estimate the correlation dynamics between all 820 bank pairs. The

Table 5.7
Differences between big banks and small banks

This table summarizes the statistics on λ_1 and λ_2 based on the size of the banks. All bank pair regressions thus fall into three separate categories: 1) both banks are big banks; 2) both banks are small banks and 3) one of the banks is considered a big bank, while the other is small.
The size of the bank is measured on the basis of the total market capitalization in the year 2000 (source: BankScope). A bank is considered big when the total market capitalization is higher than the median and smaller otherwise.

	No. of observations	No of positive obs.	In percentages of all	No of significant observations	In percentages of all	No of sign.pos obs.	In percentages of all significant obs
λ_1 (big banks only)	180	142	(78.9%)	40	(22.2%)	37	(92.5%)
λ_1 (small banks only)	191	75	(39.3%)	27	(14.1%)	5	(18.5%)
λ_1 (1 big and 1 small)	393	226	(57.5%)	38	(9.7%)	25	(65.8%)
λ_2 (big banks only)	180	108	(60.0%)	9	(5.0%)	6	(66.7%)
λ_2 (small banks only)	191	100	(52.4%)	15	(7.9%)	7	(46.7%)
λ_2 (1 big and 1 small)	393	208	(52.9%)	35	(8.9%)	23	(65.7%)

sample that we used consisted of European banks that have a continuous listing over the period 1990-2003. We realize that this procedure excludes some interesting banks, which as a result of a merger or take-over do not have a continuous listing over our sample period. We leave it to further research to deal with this issue.

Our modeling approach is motivated by the bivariate regime switch model of Ang and Bekaert (2002), who show that a regime-switch specification is very well capable to deal with different correlations over business cycle periods. Based on the combination of high/low volatility states for each pair of banks, we have 4 regimes. In each of these regimes we allow for specific correlation dynamics in the sense that they can change according a linear time trend. The regime identifying both banks being in a high volatility state is designed as to pick up increased correlations in times of financial distress by adding an additional time trend. This correlation specification is motivated by Longin and Solnik (2001). We find that in general the correlations between banks decline, but in times of high volatility the correlation increases.

In our analysis we have conditioned on a number of variables: variance, unconditional correlations, euro membership, and bank size. Since the regimes are identified on the basis of the bivariate covariance matrix, we find anticipated results when we condition on the variance and the correlation. For example, it appears that if the volatility of a bank is relatively low, the correlation with other banks decreases. We also report that there are no significant differences between banks that originate from the euro area and banks from Denmark, Sweden or the U.K.

A more interesting result is that size offers some explanation for the correlation dynamics between bank stocks in our sample. The results show that bigger banks, measured by their market capitalizations, have a tendency to become more integrated over time. Smaller banks seem to show more divergence, as shown by decreasing correlation coefficients over time. Simultaneously we find that the risk, as measured by the correlation in periods of financial distress, has not increased significantly for both bigger and smaller banks. An explanation for this result could be that the bigger banks, which are more diversified in their activities, are perceived to be more integrated by investors. Another explanation is that the bigger (institutional) investors are turning their equity portfolio strategies for the European area from a country-based style towards a sector-based style. This requires these investors to track industry indices instead of country indices. For the banking sector this would imply that these investors will focus more on the larger banks than on the smaller banks in the European area, thereby inducing a tendency for correlations to increase. An implication of this phenomenon could be that the European banks will be forced to follow either of two strategies. The first one is to remain a small and specialized bank, with activities in a regional setting. The other strategy is to integrate and become a larger player in Europe. The advantages of the latter strategy are that banks can have easier access to capital markets, leading to lower funding risk, lower costs of capital, and higher credit ratings. As a result capital market forces will help in breaking the integration paradox of European banking.

Chapter 6

Measurement of Contagion in European Banks' Equity Prices

6.1 Introduction

This chapter proposes a new methodology, which we believe may be able to identify the direction of contagion from one bank to another, given a relatively non-restrictive set of assumptions about the shocks affecting banks. The chapter builds upon the approach taken in a recent study by Bae, Karolyi and Stulz. (2003), who considered contagion among stock market returns in emerging markets. The approach is related to the growing conviction that the behavior of tail observations for financial market data is quite different from the behavior of other observations (extreme value theory).

The previous empirical literature on bank contagion has largely employed three distinct approaches: autocorrelation tests, survival time tests and event studies. Along the lines of the first approach, a number of papers have tested for autocorrelation in bank failures, controlling for macroeconomic conditions (Grossman, 1993; Hasan and Dwyer, 1994; Schoenmaker, 1996). A positive and significant autocorrelation coefficient indicates that bank failures cluster over time, given that all macroeconomic factors have been appropriately controlled for. All authors find evidence in favor of contagion, although the approach suffers from a number of inherent disadvantages. In particular, omitted macro variables, which exhibit autocorrelation would bias the results, the approach is limited by the frequency of the availability of macroeconomic data and third, the implications of the papers for today's banking system may be limited, as all papers have examined contagion in historical periods, in order to avoid problems associated with public safety nets (such as deposit insurance, lender of last resort).[67]

More recently, Calomiris and Mason (2000) examine the question whether fundamentals can explain the survival time of banks during the great depression. They find that micro, regional and national fundamentals indeed can explain a large portion of the probability of survival of banks during the great depression. There is some evidence of contagion, although it appears to have been limited to specific regions of the US.

Somewhat more closely related to the approach taken in this chapter is the quite extensive literature examining the reaction of stock prices to news (for a survey see De Bandt and Hartmann, 2002). Overall, the literature suggests that stock price reactions to news vary proportionally to the degree of the news' extent of affecting the bank. Hence, the results tend to be consistent with "information based" contagion, rather than "pure" contagion. Overall, the evidence, however, is limited to the US banking system (an exception is Gay, Timme and Yung (1991) which examine data for Hong Kong) and the approach is not well suited to distinguishing macro shocks affecting all banks simultaneously and "proper" contagion as defined above. Further, as for example Gropp, Vesala and Vulpes (2002) argue, the measure employed in these papers, namely cumulative abnormal stock market returns may not be well suited to measure certain types of shocks, such as increases in earnings volatility or leverage. In order to avoid these problems, in this chapter we consider the distance to default, which combines information on leverage, asset volatility with information contained in stock returns, in addition to using abnormal returns.

While this chapter is concerned with bank contagion, the approach followed is much more closely related to the empirical literature on financial market contagion and extreme value theory. Financial market contagion (equity markets, foreign exchanges markets and, to a more limited extent, bond markets) up until fairly recently was largely examined by testing whether the correlation between two markets increased in crisis periods (e.g. Bennett and Kelleher, 1988; King and Wadhwani, 1990; Wolf, 2000). However, Boyer, Gibson and Loretan (1997) point out that observed increases in asset price correlations during crisis periods may simply be a statistical artifact. They show that for any bivariate normal return distribution, the correlation coefficient of the two marginal distributions, conditional on the marginal distributions' standard deviations, increases with

[67] Grossman (1993) looks at US data for 1875-1914, Hasan and Dwyer (1994) consider the US free banking era (1837-1863) and Shoenmaker (1996) the years 1880-1936, also in the US.

the conditioning standard deviation. Hence, dividing a sample into crisis periods, which by definition tend to exhibit higher volatilities, and tranquil periods, which show lower volatility, will statistically result in a higher measured correlation during crisis periods, which, however, is not a reflection of contagion. Forbes and Rigobon (2002) correct for the problem and conclude that contagion during the 1987 stock market, the 1994 Mexican and the 1997 Asian crises may have been significantly overstated. Virtually all of the observed patterns can be explained by the markets' usual interdependence. Recently the Forbes and Rigobon (2002) approach has been criticized as regards to its lack of robustness with respect to omitted variable bias (Corsetti, Pericolo and Sbracia, 2002), as well as its choice of time window (Billio, Lo Duca and Pelizzon, 2002). Following this criticism, Ciccarelli and Rebucci (2003) present a Bayesian time-varying coefficient model and show that it provides improvements in the (joint) presence of heteroskedasticity and omitted variables.

Another avenue of research has been the application of extreme value theory, which concentrates on extreme co-movements, rather than examining statistical interdependence for the entire distribution. Examining interdependencies in the tails of the distribution, permits the examination of non-linearities in co-movements, as well as a relaxation of the assumption of multivariate normality of returns, which in case of fat-tailed financial market data tend to be violated (De Bandt and Hartmann, 2002; Straetmans, 2000). Hartmann, Straetmans and De Vries (2004) apply non-parametric extreme dependency measures to study extreme co-movements between stock, bond and money markets across G5 countries. They find that while the probability of a crash of the size as experienced in 1987 in the US is extremely low, the conditional probability of having a stock market crash of the size of 1987 in a G5 country, given a crash of this size in another G5 country, is significantly higher. In addition, the paper shows that the tails of the distribution exhibit substantial non-linearities relative to the entire distribution of returns. Longin and Solnik (2001) apply extreme value theory to monthly G5 equity returns between 1958 and 1996, assuming a logistic distribution function. They reject normality in the left tail (crashes), but not in the right tail (booms).[68]

In this chapter we examine contagion in a sample of 67 EU banks. For these banks we analyze the weekly first difference of the distance to default and weekly abnormal stock returns. We define contagion as one bank being hit by an idiosyncratic shock, which is transmitted to other banks. We will not specify the channel of transmission, but one could imagine money markets, payment systems, equity (ownership) links and "pure" contagion. The approach employed is quite closely related to Longin and

[68] Another strand of literature has advocated the use of GARCH models (Hamao et al., 1990; Lin et al., 1994; Susmel and Engle, 1994). Ramchand and Susmel (1998) extent the approach such that high variance and low variance states are no longer required to be drawn from the same distribution. Hence, they estimate a bivariate switching ARCH model, with the advantage that crisis episodes are endogenously determined by the data.

Solnik (2001), in the sense that we test whether the observed co-exceedances (i.e. the presence of two or more banks in the tail of the distribution simultaneously) are consistent with a multivariate normal distribution. As in Bae, Karolyi and Stulz (2003) we also examine, whether a student t distribution under different assumptions about its kurtosis is consistent with the observed patterns in the data. We find that within countries, multivariate normality can be rejected in all cases. A student t distribution may be consistent with the observed patterns in some countries but generally we cannot replicate the co-exceedances either under multivariate normality or student t assumptions. The same result is found for simulations across country pairs. The findings are strongly suggestive of non-linearities in the tails of the distribution. We argue that an appropriate way to address this finding may be a non-parametric approach. Hence, the chapter presents a simple measure of what we label "net-contagious influence." Using this method we identify banks, which appear to have been of systemic importance both for individual countries and across countries. Overall, the results suggest that there may be few banks with EU-wide systemic importance.

The chapter has implications for the ongoing debate on how to use market information for supervisory purposes and for monitoring financial stability. It is also of relevance to a better understanding of the extent to which European banking systems have become interconnected and how banking problems could spread across borders. The remainder of the chapter is organized as follows. In the next section, the calculation of our main measure of bank risk is briefly described. In section 6.3 the sample and the data used in this chapter are described, section 6.4 discusses the approach to identifying contagion employed and presents the main results. In section 6.5, we apply the methodology to identifying systemically important banks in the EU and section 6.6 concludes.

6.2 Calculation of ln(Δdd)

We use the weekly first difference of the distance to default as our measure of bank risk. In Gropp, Vesala and Vulpes (2002) it was argued that specifically with respect to banks, the distance to default may be a particularly suitable and all-encompassing measure of bank risk. In particular, the measure's ability to measure risk is not affected by the presence of explicit or implicit safety nets (unlike e.g. subordinated debt spreads). Further, it combines information about stock returns with leverage and volatility information, encompassing the most important concepts of risk (unlike e.g. unadjusted stock returns). As we are interested in the transmission of shocks from one bank to another we use the first difference of the distance to default. We calculated the distance to default for each bank in the sample and for each time period, t, using that period's equity market data. The distance to default is derived based on the Black-Scholes model, in which the time path of the market value of assets follows a stochastic process: [69]

$$\ln V_A^T = \ln V_A + \left(r - \frac{\sigma_A^2}{2} \right) T + \sigma_A \sqrt{T} \varepsilon, \qquad \textbf{(6.1)}$$

which gives the asset value at time T (i.e. maturity of debt), given its current value (V_A). ε is the random component of the firm's return on assets, which the Black-Scholes model assumes is normally distributed, with zero mean and unit variance, N(0,1).

Hence, the current distance d from the default point (where $\ln V_A^T = \ln D$) can be expressed as:

$$\begin{aligned} d &= \ln V_A^T - \ln D = \ln V_A + (r - \frac{\sigma_A^2}{2})T + \sigma_A \sqrt{T} \varepsilon - \ln D <=> \\ \frac{d}{\sigma_A \sqrt{T}} &= \frac{\ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} + \varepsilon. \end{aligned} \qquad \textbf{(6.2)}$$

That is, the distance to default, DD

$$DD \equiv \frac{d}{\sigma_A \sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \qquad \textbf{(6.3)}$$

represents the number of standard deviations that the firm is from the default point. The inputs to DD, V_A and σ_A, can be calculated from observable market value of equity capital, V_E, volatility of equity σ_E, and D using the system of equations below:

$$\begin{aligned} V_E &= V_A N(d1) - D e^{-rT} N(d2) \\ \sigma_E &= \left(\frac{V_A}{V_E}\right) N(d1) \sigma_A, \\ d1 &\equiv \frac{\ln\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \\ d2 &\equiv d1 - \sigma_A \sqrt{T}, \end{aligned} \qquad \textbf{(6.4)}$$

[69] See KMV Corporation (1999) for a similar derivation and more ample discussions.

The system of equations (6.4) is solved by using the generalized reduced gradient method to yield the values for V_A and σ_A, which in turn entered into the calculation of the distance to default. The measure of bank risk used in this study is then obtained by taking $\ln(dd_t/dd_{t-1})$, using the end of week distance to default, which in the following will be denoted as $\ln(\Delta dd)$. Hence, $\ln(\Delta dd)$ measures the percentage change in the number of standard deviations away from the default point. [70]

As underlying data we used monthly averages of the equity market capitalization, V_E from Datastream. The equity volatility, σ_E, was estimated as the standard deviation of the daily absolute equity returns and, as proposed in Marcus and Shaked (1984), we took the 6-month moving average (backwards) to reduce noise. The presumption is that the market participants do not use the very volatile short-term estimates, but more smoothed volatility measures. This is not an efficient procedure as it imposes the volatility to be constant. However, equity volatility is accurately estimated for a specific time interval, as long as leverage does not change substantially over that period (see for example Bongini, Laeven and Majnoni, 2002). The total debt liabilities, V_L, are obtained from published accounts and are interpolated (using a cubic spline) to yield weekly observations. The time to the maturing of the debt, T was set to one year, which is the common benchmark assumption without particular information about the maturity structure. Finally, we used the government bond rates as the risk-free rates, r.

6.3 Sample selection and characteristics

We started with all EU banks that are listed at a stock exchange and whose stock price and total debt are available from Datastream during January 1991 to January 2003 (92 banks). We deleted all banks that had trading volume below one thousand stocks in more than 30% of all trading days (7 banks). Furthermore, we deleted three additional banks where we had serious concerns about data quality[71] and 15 banks due to data covering less than half of the entire sample period. As will be seen below, completeness of data for each bank remaining in the sample is important, in order to avoid distortions in our measure of contagion due to few (tail) observations. The resulting sample contains 38600 week/bank observations for 67 banks, i.e. on average around 576 observations per bank (Table 6.1).

The sample contains 39 banks with maximum number of observations, given the time period considered (628) and only three banks with less than 400 observations. The minimum number of observations is 351 (Banco di Desio e della Brianza). On average the

[70] Below we will also show results for the absolute first difference in the distance to default, Δdd, and abnormal returns.
[71] The banks showed zero equity return on a high number of trading days, resulting in extremely volatile distances to default.

Table 6.1
Descriptive statistics of the distances to default

	Mean	Minimum	Maximum	Standard deviation
Distance to default	4.03	-0.29	17.11	1.88
Log-differenced DD	-0.0003	-1.47	1.25	0.031
Total assets (in billions of euro)	152.0	2.8	927.9	198.5
Number of observations	576	351	628	77.0
Number of tail observations	60.1	20	125	28.6

banks in the sample are just above four standard deviations away from the default point (a mean distance to default of 4.03). However, this hides substantial variation in the health of banks. Banco di Napoli represents the minimum with a distance of default dipping below zero at -0.29, suggesting that the bank was in default. No other banks exhibit negative distances to default in the sample; Banco Espaniol de Credito (Spain), Bankgesellschaft Berlin (Germany), Sampo Leonia (Finland), SEB (Sweden) all show distances to default below one and all are well known to have experienced significant difficulties during the period under consideration in this chapter. At the other end of the spectrum, there were 14 banks with a maximal distance to default of above 10. Interesting the global maximum of 17.11 is attributable to the same bank that also experienced the global minimum: Banca di Napoli. The mean of the first difference in the distance to default is approximately zero, the largest negative change is about –4, which given a mean level of 4 can truly be considered a sizeable weekly shock.

The banks in the sample are generally quite large. On average, total assets amount to EUR 152 billion. The relatively large average size is an outcome of the requirement for the bank to be traded at a stock exchange. Nevertheless, the size variation is considerable within the sample. For example, the largest bank, Deutsche Bank, is 300 times the size of the smallest, Banco Desio e della Brianza. Table 6.2 gives all banks in the sample, ranked by total assets. The table suggests that in most countries, the largest banks are covered, although there are some notable exceptions, such as Belgium, where Dexia and Fortis both had to be excluded due to data limitations. This results in an above 50 percent coverage of total banking assets in the EU, despite the fact that in numbers the sample contains less than 1 percent of all EU banks (Table 6.3). The degree of coverage in each country depends on the number of banks traded at a stock exchange and the structure (especially concentration) of the banking system. The sample contains banks from all EU countries except Luxembourg. The ranking of all banks by total assets (with the largest bank in each country in bold) is also presented, because it permits a check of all results presented subsequently in the chapter. Clearly, the naïve approach to determining within country

Table 6.2
Sample banks (sorted by total assets in 2000, millions of euro)

1	Deutsche Bank	DE	927,900
2	BHVB		694,300
3	BNP Paribas	FR	693,053
4	ABN AMRO	NL	543,200
5	Barclays	UK	486,936
6	Dresdner Bank		482,600
7	Societe Generale		455,881
8	Commerzbank		454,500
9	ING		406,393
10	Banco Santander Central Hispano	ES	347,288
11	Banca Intesa	IT	331,364
12	National Westminster		294,695
13	Abbey National		293,395
14	BBVA		292,557
15	HSBC		288,339
16	Royal Bank of Scotland		206,176
17	Bankgesellschaft Berlin		203,534
18	UniCredito Italiano		202,649
19	Danske Bank	DK	182,520
20	KBC Bank	BE	176,909
21	Sanpaolo IMI		171,046
22	Bank Austria	AT	164,669
23	Standard Chartered		161,964
24	DePfa Group		156,446
25	Bank of Scotland		136,288
26	Banca di Roma		132,729
27	Skandinaviska Enskilda Banken (SEB)	SE	118,261
28	Natexis Banques Populaires		113,131
29	Svenska Handelsbanken		112,804
30	Allied Irish Banks	IE	77,932
31	Bank of Ireland		73,859
32	Banco Comercial Portugues	PT	61,850
33	BHF-BANK		53,863
34	Rolo Banca 1473		47,044
35	Banco Espanol de Credito		44,381

(continued on next page)

continued

36	Banca Popolare di Bergamo		37,670
37	Banco di Napoli		34,361
38	Banca Popolare di Lodi		34,223
39	Creditanstalt		34,040
40	Banco Espirito Santo		33,862
41	Sampo Leonia	FI	32,795
42	IKB Deutsche Industriebank		32,359
43	Banco Popular Espanol		31,288
44	Alpha Bank	GR	30,183
45	Banca Popolare di Milano		28,282
46	Okobank		27,086
47	Banca Lombarda		26,816
48	Banco Totta e Acores		23,166
49	BPI-SGPS		21,906
50	Banca Popolare di Novara		20,959
51	Banca Popolare Commercio e Industria (BPCI)		20,911
52	Jyske Bank		17,044
53	Commercial Bank of Greece		16,164
54	Credito Emiliano		15,148
55	Anglo Irish Bankcorp		11,047
56	Banca Agricola Mantovana		10,190
57	Banco Pastor		9,404
58	CPR		8,616
59	Credito Valtellinese		7,416
60	Banco Guipuzcoano		5,518
61	Kas-Associatie		5,417
62	Banco Zaragozano		5,175
63	Schroders		4,180
64	Banca Popolare di Intra		3,929
65	Close Brothers		3,241
66	Singer & Friedlander Group		2,792
67	Banco di Desio e della Brianza		2,776

Table 6.3
Sample composition and coverage by country

The total assets of banks in the sample

Country	Number of banks	Percentage of total assets of commercial banks
Austria	2	35.3%
Belgium	1	22.7%
Germany	8	55.4%
Denmark	2	85.3%
Spain	7	68.3%
Finland	2	43.5%
France	4	36.2%
Greece	2	33.4%
Ireland	3	44.0%
Italy	17	59.5%
The Netherlands	3	58.9%
Portugal	4	53.7%
Sweden	2	79.2%
United Kingdom	10	72.8%
Total	67	53.9%

systemically important banks would be to pick the largest bank(s) in each country and for the EU as a whole, the largest banks in the EU.

As the first step we calculated the full correlation matrix of ln(Δdd) for all banks in the sample.[72] As expected, within country correlations are higher than across country correlations. For example in Germany, BHVB correlation with Deutsche Bank, Dresdner Bank and Commerzbank are around 0.7, the correlation between Deutsche Bank and Dresdner Bank is 0.86. Similarly, the correlation between the distribution of ING and ABN Amro in the Netherlands is 0.6. The correlation in ln(Δdd) among UK banks is also high, in many cases above 0.5. However, in some cases within country correlations among banks are much lower, i.e. in Italy where most correlations cluster around 0.2, as well as in Portugal, Sweden and Austria. In Spain, we have some banks that show quite high correlations, especially involving BBVA, whose Δdd shows a correlation of 0.6 with Banco Santander and 0.5 with Banco Popular Espanol. Most other Spanish banks show correlations that range between just above zero and 0.2.

[72] The matrix is not presented due to space limitations, but is available upon request.

Again as one would expect, correlations are also generally quite low for cross-country bank pairs. Of the 4489 cross-country correlations, only around 60 (less than 2 percent) are above 0.3. High correlations exist between German and some Spanish banks, between the largest French and Spanish banks, between Dutch and German, as well as Dutch and Irish banks. Interestingly, some banks tend show negative correlations with most banks in the sample. These include Banco di Napoli and Okobank, both of which experienced substantial difficulties during the sample period.[73]

As we have argued above, the study of correlations may be misleading or uninformative in a number of respects. Correlations may not be constant during crisis times, precisely when they would be of particular interest. It has been well established that the behavior of tail observations for financial market data is quite different from the behavior of other observations. In addition, we are specifically interested in distinguishing contagion, as opposed to common shocks affecting banks simultaneously. We define contagion as one bank being hit by an idiosyncratic shock, which then is transmitted to other banks. Correlations, by definition, will not be able to distinguish the two, unless one attempts to fully control for common (macro) shocks. Related to this, in the case of banks in particular, the *direction* of contagion is of interest, i.e. which bank may have systemic importance for other banks.

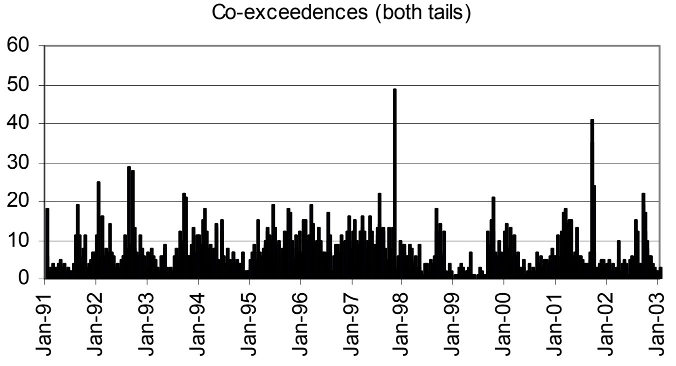
For these reasons, in this chapter we follow Bae, Karolyi and Stulz (2003) and focus on co-exceedances in the tails of the distribution of $\ln(\Delta dd)$. We count the number of periods at least one bank's $\ln(\Delta dd)$ is in the tail of the distribution ("exceedance") and, more importantly, the number of periods more than one bank is in the tail of the distribution ("co-exceedance"). We arbitrarily define a tail event as one in the 5 percent (positive and negative) tail of the distribution. Figure 6.1 shows the number of tail events per week: panel A shows the histogram of both tails simultaneously, while panel B and panel C represent the number of tail events in the positive and negative tail respectively. The histograms show that the tail events are not evenly spread over the sample period. The maximum number of co-exceedances is reached in the first week of November 1997, when 49 (out of 67) banks have a big (negative) change in their distance to default.
In Table 6.4 we report the counts of the number of co-exceedances within countries. For the within country exercise to be meaningful, we were limited to countries with at least three banks. Hence, no figures are provided for banks in Austria, Belgium, Denmark, Finland, Greece and Sweden.[74]

[73] As we will see below, idiosyncratic shocks facing each bank are crucial in order to identify contagion. This issue will be revisited below.
[74] Note that the banks in these countries will, however, be considered when we examine systematically important banks below.

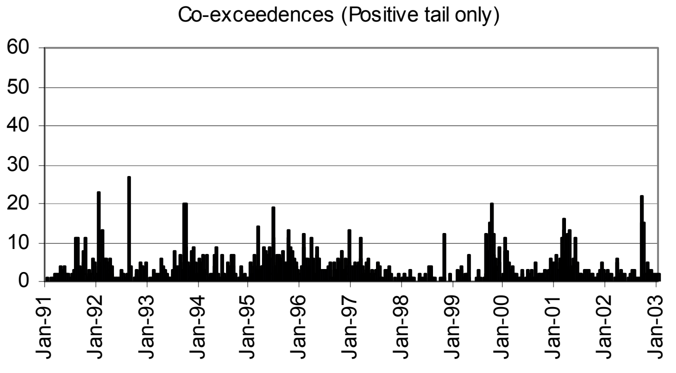
Figure 6.1
Histogram of tail events

This figure shows the number of tail events per week in ln(*Δdd*). The tail is defined as the 5% largest (positive tail) and smallest (negative tail) observations of the distribution of ln(*Δdd*). Panel A shows the histogram of both tails simultaneously. Panel B and panel C represent the number of tail events in the positive and negative tail respectively.

Panel A



Panel B



Panel C

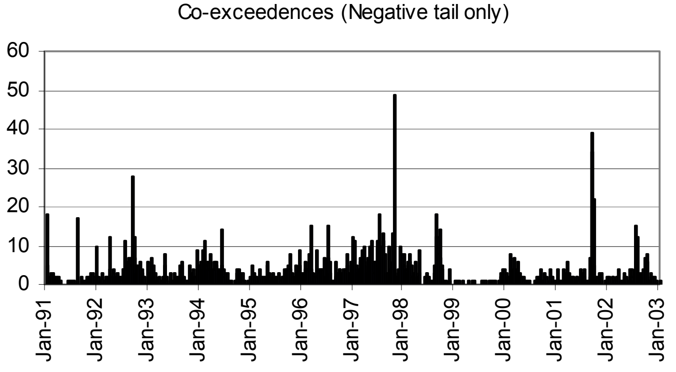


Table 6.4
Summary statistics of (co-)exceedances for weekly log-differenced distance to defaults for EU banks

Number of (co-) exceedances in the bottom tails							
	>6	5	4	3	2	1	0
DE (8 banks)	3	3	8	9	20	79	416
ES (7 banks)	1	1	5	11	29	98	483
FR (3 banks)	-	-	-	2	15	29	384
IE (3 banks)	-	-	-	7	15	43	563
IT (10 banks)	5	3	5	10	36	114	403
NL (3 banks)	-	-	-	3	11	40	418
PT (4 banks)	-	-	3	7	9	46	420
UK (7 banks)	0	6	1	6	33	102	480
Number of (co-) exceedances in the top tails							
	>6	5	4	3	2	1	0
DE (8 banks)	1	3	6	9	29	83	407
ES (7 banks)	0	2	7	12	22	102	483
FR (3 banks)	-	-	-	3	11	34	382
IE (3 banks)	-	-	-	4	13	56	555
IT (10 banks)	5	2	8	18	27	105	411
NL (3 banks)	-	-	-	7	2	46	417
PT (4 banks)	-	-	1	5	11	56	412
UK (7 banks)	1	0	6	10	25	109	477

For the following, we also limit the sample to banks for which we have at least 500 concurrent observations; this is necessary for the simulations reported below.[75] Let us examine co-exceedances within countries first. The maximum number of co-exceedances is naturally constrained by the number of banks for which we have observations. From this perspective, Germany, Italy, and the UK are the most interesting countries, as we have 8, 10 and 7 banks in the sample, respectively. Considering only these three countries, one is immediately struck by the fact that Germany and Italy have 6 and 8 weeks, during which 5 or more banks were in the bottom tail and 4 and 7 weeks, respectively, in which 5 or more banks were in the top tail. In contrast, the corresponding figures for Spain are 2 and 2 weeks. Recall that the correlations among banks of ln(Δdd) considering the entire distribution were higher in Germany and Spain compared to Italy. Next, consider the three countries with three banks (France, Ireland and the Netherlands) together with Portugal, which has 4 banks in the sample. Ireland and Portugal have substantially more weeks, in which all three (or more, in case of Portugal) banks were in the bottom tail compared to the

[75] The requirement will be relaxed in section 6.5 of this chapter.

other two countries. Furthermore, there are considerable asymmetries with respect to bottom and top tail co-exceedances. In Ireland, for example, there are seven weeks, in which all three Irish banks experienced a bottom tail event, but only four weeks in which all three banks had a top tail event. Also, in the UK bottom tail co-exceedances are more frequent than top tail co-exceedances, as there is only one week with five banks co-exceeding in the top tail, but six such cases in the bottom tail.

We are also interested in cross-border contagion. Hence, we performed the same exercise of counting co-exceedances for bilateral country pairs of the largest EU countries (Germany, Spain, France, Italy and the UK). The results are reported in Table 6.5. For ease of presentation, we report co-exceedances if at least one bank from each country is in the tail in a given week. Hence, the category "5 co-exceedances" for the UK-FR country pair contains at least one bank each from the UK and France, but we do not distinguish between whether there are four French banks and one UK bank or four UK banks and one French bank. Overall, there are a substantial number of weeks with more than five banks concurrently in the tail. Excluding the country pairs with France, which given the low number of French banks in the sample are not strictly comparable, this figure varies from 6 (Spain-UK) to 16 (Germany-Spain) for the bottom tails and from 7 (Spain-UK) to 20 (Spain-Italy) for the positive tails. For the country pairs involving France, five or more banks are in the bottom tail 5-7 weeks, in the top tail 3 to 9 weeks. This high variation in itself may suggest that there are differences across country pairs, although clearly this may be due to common shocks hitting banks in the two countries simultaneously as much as to contagion. Looking across the table, one also notices that in some cases the frequency of bottom tail co-exceedances appears to be quite different from the one in the top tail, although no strong patterns emerge.

In summary, both the relatively high number of co-exceedances and the asymmetry in bottom and top tail co-exceedances are suggestive that the correlation among banks may not be constant during "extreme" times. In the following section, we compare the observed co-exceedances with those generated by Monte Carlo simulations under standard distributional assumptions.

6.4 Identification of contagion

6.4.1 Co-exceedance and Monte Carlo evidence

Suppose that the variance/covariance matrix of $\ln(\Delta dd)$ is stationary over the sample period and that the returns follow a multivariate Normal or student t distribution. Using that variance-covariance matrix, we simulate 1000 random realizations of the time series of weekly realizations of $\ln(\Delta dd)$. In order to limit computations, rather than simulate the joint distribution of all 67 banks, we simulated country pair by country pair. For each

Table 6.5
Summary statistics of (co-)exceedances for weekly log-differenced distance to defaults for EU banks, cross-country evidence

In parenthesis the number of banks in each country. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances does not preclude that many banks in one country can be in the tail simultaneously. The number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used.

Number of (co-) exceedances in the bottom tails							
	>6	5	4	3	2	1	0
ES-UK (7,7)	5	1	6	10	30		576
ES-DE (7,8)	10	6	9	8	7		498
ES-FR (7,3)	3	3	4	5	7		408
ES-IT (7,10)	8	2	4	18	24		520
DE-UK (8,7)	9	2	9	6	8		504
DE-FR (8,3)	5	2	2	4	5		384
DE-IT (8,10)	10	3	8	9	15		493
FR-UK (3,7)	4	1	4	3	4		414
FR-IT (3,10)	5	1	4	6	6		408
UK-IT (7,10)	10	3	6	12	19		526
Number of (co-) exceedances in the top tails							
	>6	5	4	3	2	1	0
ES-UK (7,7)	0	7	5	11	24		581
ES-DE (7,8)	10	4	9	10	11		494
ES-FR (7,3)	3	02	4	2	7		412
ES-IT (7,10)	11	9	8	12	24		512
DE-UK (8,7)	4	6	9	14	16		489
DE-FR (8,3)	1	5	2	5	9		380
DE-IT (8,10)	11	5	5	12	22		483
FR-UK (3,7)	1	2	3	7	7		410
FR-IT (3,10)	5	4	3	1	11		406
UK-IT (7,10)	9	5	11	7	22		522

realization, we identify the 5 percent tail for the bottom tail and the top tail separately and perform a non-parametric count across banks within countries. This process yields a set of simulated exceedances (one bank in the tail) and co-exceedances (two or more banks in the tail), which we can compare to the number of exceedances and co-exceedances in the actual data.

The distribution of the co-exceedances will depend on the assumptions made about the data generating process. We perform Monte Carlo simulations under three assumptions: The data have been generated by a multivariate normal distribution, by a student t distribution with 5 degrees of freedom or by a student t distribution with 10 degrees of freedom.[76] The results of this exercise are reported in Table 6.6 for each country separately. We, as before, limited ourselves to countries with three or more banks. We find that the multivariate Normal distribution is unable to replicate the number of co-exceedances in the actual data for any of the banks in the countries we study, regardless of whether we consider positive or negative co-exceedances. Even more striking, in some countries, the student t distribution with 5 degrees of freedom, i.e. under fairly strong assumptions about kurtosis, is unable to generate the number of co-exceedances in the data or if it is, is unable to replicate the number of single exceedances.

Let us consider the countries with at least 7 banks first. The multivariate Normal distribution generates zero weeks with five or more co-exceedances for Spain, the UK, and Italy for both tails, while the actual figures are 2, 6 and 8 weeks for the bottom tail and 2, 1 and 7 weeks for the top tail, respectively. In Germany the Normal distribution, due to the higher correlations among banks, generates 3 weeks with five or more co-exceedances in both tails, which compares to 6 (4) weeks for bottom (top) tails in the data. In general, in the case of Germany, the Normal distribution comes closest of all countries to replicating the actual data. In Ireland, France, and the Netherlands, there are only three banks in the sample. The Normal distribution generates 1.7, 0.9 and 1.1 weeks, respectively, in which all of these banks are simulated to be in the bottom tail. This compares to 7, 2 and 3 weeks in the data. The figures for the top tails look quite similar.

The student t distribution yields simulation results closer to the actual data. For example, the German and Spanish co-exceedances for both tails can largely be replicated assuming a student t distribution with 10 degrees of freedom. In countries with 3 or 4 banks, we find that the student t distribution with 5 degrees of freedom is able to replicate the results for both tails in France and Portugal and for bottom tails in the Netherlands and the top tails in Ireland. Nevertheless, the results overall suggest that in most countries it is exceedingly difficult to replicate the distribution of co-exceedances. Looking at the 95 percent confidence bands of the simulated distributions, we can reject equality for all countries at least for some level of co-exceedance for the Normal distribution and for many in case of the student t distributions.

[76] The degrees of freedom in a student t distribution equal N+K-1, where N is the number of banks (8 for Germany, 7 for Spain, 3 for France, 3 for Ireland, 10 for Italy, 3 for the Netherlands, 4 for Portugal and 7 for the UK) and where K can be set from 1 (significant positive excess kurtosis) to 25 (little excess kurtosis, approximating Normal). We also explored scenarios with lower values for K, but found them to vastly understate the number of cases with co-exceedances of less than 3 banks. Bae et al. (2003) report also scenario's using a multivariate GARCH approach, but find that it also is unable to generate the number of co-exceedances in their sample of emerging market stock returns.

Table 6.6

Monte Carlo Simulations of co-exceedances of weekly logdifferenced distance to default for EU banks

Reported are the mean numbers of co-exceedances under the different distributional assumptions, given the actual covariance matrix. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
DE (8 banks)	*3*	*3*	*8*	*9*	*20*	*79*	*416*	*407*	*83*	*29*	*9*	*6*	*3*	*1*
Normal	**0.70**	1.48	**3.52**	7.93	26.29	**112.78**	**385.29**	**385.62**	**112.32**	26.43	7.85	3.50	1.60	0.69
Student t(5)	3.31	4.26	7.26	11.43	22.66	**63.94**	425.14	**424.97**	**64.21**	22.56	11.53	7.17	4.22	3.34
Student t(10)	2.22	3.63	6.57	11.52	24.14	73.71	416.21	416.32	73.63	24.06	11.59	6.51	3.63	2.27
ES (7 banks)	*1*	*1*	*5*	*11*	*29*	*98*	*483*	*483*	*102*	*22*	*12*	*7*	*2*	*0*
Normal	**0.00**	**0.01**	**0.08**	**0.95**	**16.68**	**183.43**	**426.85**	**426.04**	**184.84**	16.25	**0.81**	**0.05**	**0.00**	0.00
Student t(5)	0.55	1.64	4.93	12.35	30.33	91.00	487.20	487.14	90.99	**30.50**	12.29	4.86	1.68	0.54
Student t(10)	0.23	0.99	3.72	10.91	30.68	104.67	476.80	477.10	104.16	**30.90**	10.86	3.67	1.07	0.24
FR (3 banks)	-	-	-	*2*	*15*	*29*	*384*	*382*	*34*	*11*	*3*	-	-	-
Normal				0.94	11.22	**39.72**	**378.11**	377.69	41.68	9.57	1.06			
Student t(5)				2.32	11.07	35.90	380.71	381.34	35.56	10.85	2.25			
Student t(10)				1.74	10.45	**38.90**	**378.92**	379.71	38.24	10.41	1.65			
IE (3 banks)	-	-	-	*7*	*15*	*43*	*563*	*555*	*56*	*13*	*4*	-	-	-
Normal				**1.66**	11.76	**65.51**	**549.08**	**549.17**	65.43	11.65	1.76			
Student t(5)				**3.41**	14.91	**53.96**	**555.73**	555.54	54.28	14.82	3.36			
Student t(10)				**2.44**	14.02	**58.62**	**552.91**	553.16	58.26	14.01	2.57			
IT (10 banks)	*5*	*3*	*5*	*10*	*36*	*114*	*403*	*411*	*105*	*27*	*18*	*8*	*2*	*5*
Normal	**0.16**	**0.54**	2.21	9.40	41.15	**164.97**	**357.59**	**356.62**	**166.14**	**41.32**	**9.22**	**2.09**	0.48	**0.13**
Student t(5)	2.90	3.85	7.99	**16.62**	36.28	**95.47**	412.89	413.26	95.10	**36.25**	16.53	8.06	3.87	2.93
Student t(10)	**1.54**	2.79	6.73	15.82	38.92	111.97	398.24	**397.78**	112.62	**39.04**	15.51	6.70	2.78	**1.58**
NL (3 banks)	-	-	-	*3*	*11*	*40*	*418*	*417*	*46*	*2*	*7*			
Normal				1.05	6.89	**54.06**	**410.00**	**407.57**	**58.58**	5.11	**0.73**			
Student t(5)				2.58	11.81	39.63	417.98	418.06	39.37	**12.06**	**2.5**			
Student t(10)				1.78	11.32	43.04	415.87	415.90	43.03	**11.25**	**1.82**			
PT (4 banks)	-	-	*3*	*7*	*9*	*46*	*420*	*412*	*56*	*11*	*5*	*1*	-	-
Normal			0.11	**1.08**	7.41	**78.51**	**397.89**	**396.83**	**80.48**	**6.66**	**0.94**	0.10		
Student t(5)			**0.77**	4.17	14.10	53.21	**412.75**	413.04	52.79	14.11	4.24	0.82		
Student t(10)			**0.49**	**3.34**	13.44	**58.14**	**409.59**	409.69	57.97	13.48	3.40	0.47		
UK (8 banks)	*0*	*6*	*1*	*6*	*33*	*102*	*480*	*477*	*109*	*25*	*10*	*6*	*0*	*1*
Normal	0.04	**0.18**	0.85	4.40	28.79	**144.69**	**449.05**	**450.86**	**142.12**	28.77	**4.96**	**1.00**	0.24	**0.04**
Student t(5)	0.84	**2.28**	**5.78**	**12.43**	28.96	**85.19**	**492.54**	**492.31**	**85.42**	28.97	12.62	5.60	2.25	0.83
Student t(10)	0.39	**1.52**	4.54	**11.32**	29.87	98.14	482.22	482.90	97.14	30.00	11.40	4.62	1.50	0.43

Table 6.6a

Monte Carlo Simulations of co-exceedances of weekly first differenced distance to default for EU banks

Reported are the mean numbers of co-exceedances under the different distributional assumptions, given the actual covariance matrix. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
DE (8 banks)	*4*	*1*	*5*	*18*	*17*	*77*	*416*	*402*	*93*	*26*	*8*	*4*	*2*	*3*
Normal	**0.78**	2.29	5.09	**10.82**	**24.88**	**96.20**	**397.95**	395.78	99.45	24.47	10.47	4.89	2.13	**0.81**
Student t(5)	3.74	**4.51**	7.34	**11.24**	21.47	**62.55**	**427.15**	**427.78**	**61.92**	21.41	11.14	7.32	4.54	3.89
Student t(10)	2.72	4.02	7.00	**11.24**	22.70	70.57	419.75	**419.70**	**70.63**	22.69	11.22	7.06	4.00	2.71
ES (7 banks)	*1*	*0*	*3*	*9*	*26*	*123*	*466*	*478*	*107*	*26*	*8*	*8*	*1*	*0*
Normal	**0.00**	0.00	**0.01**	**0.67**	**18.91**	**180.15**	**428.27**	**428.40**	**179.90**	**19.02**	**0.67**	**0.02**	**0.00**	0.00
Student t(5)	0.35	1.47	4.51	11.91	30.55	**95.85**	**483.46**	483.30	96.12	30.48	11.69	4.61	1.44	0.36
Student t(10)	0.12	0.81	3.17	10.39	30.50	110.40	472.61	472.38	110.78	30.44	10.24	**3.30**	0.73	0.13
FR (3 banks)	-	-	-	*3*	*9*	*38*	*380*	*378*	*40*	*11*	*1*	-	-	-
Normal				0.97	7.21	**47.67**	**374.15**	**372.95**	**50.89**	**5.38**	0.79			
Student t(5)				1.99	10.76	37.51	379.74	380.29	37.38	10.36	1.97			
Student t(10)				1.50	10.04	40.42	378.04	378.67	40.16	9.69	1.49			
IE (3 banks)	-	-	-	*7*	*14*	*45*	*562*	*553*	*59*	*13*	*3*	-	-	-
Normal				**1.40**	14.96	**59.87**	**551.77**	551.82	59.80	14.94	1.44			
Student t(5)				3.63	15.03	53.07	556.58	556.49	52.74	15.04	3.73			
Student t(10)				**2.89**	14.23	**56.86**	**554.02**	553.77	57.24	14.21	2.78			
IT (10 banks)	*4*	*4*	*3*	*12*	*39*	*114*	*400*	*398*	*115*	*38*	*12*	*7*	*3*	*3*
Normal	**0.00**	**0.00**	**0.05**	**2.66**	38.78	**202.24**	**332.26**	**332.88**	**201.02**	39.38	**2.68**	**0.05**	**0.00**	**0.00**
Student t(5)	2.49	3.76	**7.94**	16.50	37.00	**97.69**	410.60	**410.42**	**98.06**	36.91	16.49	7.83	3.71	2.58
Student t(10)	**1.30**	2.53	6.27	15.61	39.59	115.99	394.71	394.88	115.77	39.62	15.54	6.35	2.56	1.28
NL (3 banks)	-	-	-	*1*	*13*	*42*	*416*	*417*	*44*	*6*	*5*	-	-	-
Normal				0.56	**4.76**	**59.81**	**406.87**	**405.09**	**63.22**	3.28	**0.41**			
Student t(5)				1.99	11.28	42.47	416.26	416.21	42.60	**11.17**	**2.02**			
Student t(10)				1.47	10.66	45.30	414.59	414.29	45.85	**10.44**	**1.43**			
PT (4 banks)	-	-	*2*	*5*	*11*	*52*	*415*	*409*	*61*	*10*	*4*	*1*	-	-
Normal			**0.08**	**1.13**	9.59	**74.12**	**400.08**	**399.58**	**74.96**	9.40	**0.99**	0.07		
Student t(5)			0.62	3.87	14.07	54.80	411.65	411.47	55.10	14.04	3.78	0.62		
Student t(10)			0.37	2.81	13.22	60.65	**407.95**	407.98	60.65	13.15	2.85	0.38		
UK (8 banks)	*1*	*1*	*5*	*2*	*29*	*125*	*465*	*467*	*124*	*24*	*8*	*3*	*1*	*1*
Normal	**0.00**	**0.00**	**0.02**	1.12	22.69	**171.21**	**432.97**	**433.61**	**170.06**	23.07	**1.25**	**0.01**	**0.00**	**0.00**
Student t(5)	0.66	1.96	5.37	**12.32**	29.47	**88.79**	**489.44**	**489.88**	**88.15**	29.49	12.46	5.39	1.99	0.66
Student t(10)	0.32	1.28	4.10	**11.19**	30.13	**101.41**	**479.57**	**479.51**	**101.55**	30.02	11.20	4.17	1.24	0.32

Table 6.6b

Monte Carlo Simulations of co-exceedances of weekly abnormal returns distance to default for EU banks

Reported are the mean numbers of co-exceedances under the different distributional assumptions, given the actual covariance matrix. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
DE (8 banks)	*0*	*2*	*2*	*13*	*32*	*115*	*426*	*428*	*107*	*43*	*7*	*4*	*0*	*1*
Normal	0.02	**0.21**	1.21	**6.48**	32.30	**145.95**	**403.83**	**404.40**	**144.84**	**32.82**	6.50	**1.22**	0.20	**0.03**
Student t(5)	0.70	1.78	4.94	12.89	33.34	**97.63**	**438.72**	**439.24**	96.85	**33.55**	**12.78**	5.04	1.88	0.67
Student t(10)	0.25	0.97	3.48	11.05	34.14	114.24	425.87	426.41	113.38	34.34	11.11	3.52	0.99	0.26
ES (7 banks)	*0*	*0*	*3*	*9*	*41*	*117*	*511*	*504*	*125*	*44*	*7*	*1*	*0*	*0*
Normal	0.00	0.02	**0.27**	**3.18**	**27.81**	**171.71**	**478.03**	**477.58**	**172.36**	**27.81**	**2.99**	0.24	0.02	0.00
Student t(5)	0.13	0.73	3.05	10.99	35.64	117.11	513.35	513.39	116.92	35.79	11.05	3.05	0.68	0.13
Student t(10)	0.03	0.28	1.62	8.18	35.02	**135.34**	**500.52**	500.04	136.12	**34.91**	8.02	1.61	0.28	0.03
FR (3 banks)	-	-	-	*1*	*14*	*41*	*427*	*429*	*39*	*12*	*3*	-	-	-
Normal				0.64	9.50	**51.07**	**421.79**	**422.13**	50.46	9.69	**0.72**			
Student t(5)				1.80	11.05	44.50	425.65	426.17	43.51	11.48	1.85			
Student t(10)				1.30	10.34	47.42	423.94	424.06	47.10	10.61	1.23			
IE (3 banks)	-	-	-	*0*	*13*	*76*	*592*	*588*	*85*	*7*	*1*	-	-	-
Normal				0.37	**6.40**	**88.11**	**586.13**	586.28	87.83	6.51	0.39			
Student t(5)				1.59	12.78	71.67	594.96	**594.93**	**71.67**	**12.88**	1.52			
Student t(10)				0.96	11.00	77.13	591.92	591.71	77.50	10.88	0.91			
IT (10 banks)	*4*	*5*	*4*	*6*	*48*	*161*	*453*	*455*	*164*	*34*	*16*	*5*	*3*	*4*
Normal	**0.10**	**0.55**	2.75	**13.04**	52.88	**181.78**	**429.91**	**430.42**	181.12	**52.76**	13.20	2.90	**0.51**	**0.11**
Student t(5)	2.60	4.02	**8.93**	**19.99**	45.36	**117.58**	**482.52**	**482.68**	**117.15**	**45.68**	19.88	9.03	4.00	2.58
Student t(10)	**1.19**	2.48	7.02	**18.64**	48.81	**139.50**	463.38	463.26	**139.48**	**49.15**	18.51	6.93	2.49	**1.18**
NL (3 banks)	-	-	-	*1*	*15*	*60*	*544*	*533*	*82*	*4*	*1*	-	-	-
Normal				0.20	**5.43**	**81.54**	**532.83**	532.65	81.91	5.24	0.20			
Student t(5)				1.04	11.30	67.29	540.37	**540.26**	**67.50**	**11.22**	1.02			
Student t(10)				0.55	**9.70**	**71.94**	537.81	537.52	**72.52**	**9.41**	0.56			
PT (4 banks)	-	-	*0*	*0*	*10*	*61*	*332*	*337*	*54*	*9*	*3*	*0*	-	-
Normal			0.01	0.36	6.53	66.83	329.27	**329.28**	**66.79**	6.60	**0.33**	0.01		
Student t(5)			0.12	1.41	10.17	55.93	335.36	335.62	55.52	10.25	1.47	0.14		
Student t(10)			0.05	0.84	8.60	61.08	332.43	332.35	61.27	8.47	0.87	0.05		
UK (8 banks)	*0*	*0*	*3*	*13*	*31*	*125*	*509*	*507*	*128*	*33*	*9*	*3*	*1*	*0*
Normal	0.01	0.08	0.77	**5.51**	32.93	**152.08**	**489.62**	**489.85**	**151.71**	32.96	5.63	**0.76**	0.08	0.01
Student t(5)	0.21	0.98	3.61	11.78	35.53	110.95	517.94	**517.65**	**111.53**	35.53	11.74	3.52	0.98	0.22
Student t(10)	0.06	0.46	2.09	9.27	35.07	128.99	505.06	504.99	129.03	35.08	9.31	2.12	0.41	0.06

We wanted to check whether this result would extend to other measures of bank risk. We report the results for the first differenced distance to default in Table 6.6a. Conceptually, the simple first difference in the distance to default reflects shocks, which are large in absolute terms. This has the consequence, however, that banks, which are already close to the default point, by construction, cannot experience a tail event, as the distribution of the level distance to default is truncated at zero. The log-differenced distance to default highlights percentage changes, which avoids the problem of truncation. However, to the extent that our measure is noisy, for banks close to the default point we may be interpreting noise as tail events.

Table 6.6a is organized exactly as Table 6.6 above. Comparing the two tables it turns out that the results are very similar. As before, a multivariate normal distribution is not able to replicate our counts of co-exceedances. The fatter-tailed student t-distribution does a better job in this respect. For example, both measures suggest equal frequencies of weeks in which at least five banks were concurrently in the tail (in countries with at least 5 banks). More formally, we examined whether applying the first-differenced simulation results to the log-differenced actual co-exceedances would have resulted in more or less rejections of the simulated co-exceedances. We found this not to be the case, the only exception being the UK in the case of negative tail co-exceedances. In addition, we checked whether the measures pick up the same exact weeks with a high number of exceedances and whether the banks with an exceedance are the same. Again we found this to be the case.[77]

For the second robustness check we use abnormal returns, which we obtained by using the residuals from the following standard one factor model:

$$R_{it} = \alpha_0 + \alpha_1 M_{ct} + \varepsilon_{it} \tag{6.5}$$

where R_{it} denotes the weekly log return of bank i in week t and M_{ct} denotes the weekly log return of the broad market index of the country c, where bank i is headquartered. The estimated residuals $\hat{\varepsilon}_{it}$ are then the abnormal returns of bank i. Results from estimating equation (6.5) are given in Appendix 6.A. The estimated coefficient on α_1 ("beta") is of particular interest. On average, it is 0.89, with a maximum of 1.58 (Standard Chartered) and a minimum of 0.22 (Banco Guipuzcoano). In all cases, the coefficient is significant at the one percent level. On average, the market portfolio explains around a third of the total variation in log weekly returns (R^2 = 0.32).

[77] In most cases the number of extreme observations was approximately the same and deviations were small, i.e. no more than one bank. For example, looking at the negative tail for Italy, during weeks with 6 or more banks in the tail in the first differences of the distance to default distribution (Table 6.6), there were at least 4 banks in the tail of the log difference distribution. The same holds for the positive tail: the two extra observations in table 6.6a, had respectively 5 and 4 banks in the tails when the first difference of the distances to default was used.

Table 6.7
Descriptive statistics for first differenced distance to default and abnormal returns

	Mean	Minimum	Maximum	St. deviation
Δ Distance to default	-0.001	-3.97	6.69	0.15
Abnormal returns	0.000	-94.20	131.94	3.75
Number of observations	647	402	681	69.73
Number of tail observations	65	20	153	30.7

Descriptive statistics for the resulting abnormal returns are given in Table 6.7. Notice that the number of observations is higher (647 versus 576), since some data were lost in the calculation of stock price volatility used as in input in the distance to default and there were missing values for other inputs. The mean for the abnormal returns is equal to zero, as expected. The minimum and maximum are quite high and are caused by exceptional cases: the maximum is due to Banca di Napoli in January 1998 and the minimum is due to Banco Espanol de Credito in February 1994. Note that outliers should not be a problem, given that we consider the presence in the tail rather than the absolute size of returns.

The comparison between the actual abnormal return data and the simulations are reported in Table 6.6b, which is constructed in the same way as Tables 6.6 and 6.6a above. It shows that we observe significantly fewer instances, in which many banks experienced a bottom tail event concurrently, compared to the other two measures. This is not entirely surprising, because we have eliminated at least some macro shocks as a source for the concurrent presence in the tail of the distribution of more than one bank. It is striking, however, to observe that as for the two measures used before, the normal distribution is unable to replicate the observed frequencies of co-exceedances. Further, even when assuming fat tailed distributions such as the student t distribution with 5 and 10 degrees of freedom, in many countries we can reject that such distributions adequately describe the observed patterns. Note one important conceptual difference between the distance to default and abnormal returns. The distance to default is declining in the volatility of the underlying assets, while returns are increasing in asset volatility (see Goh and Ederington, 1993; Gropp, Vesala and Vulpes, 2003 and Gropp and Richards, 2001), due to the call option characteristic of the stock price.[78] While we examine results for abnormal returns

[78] The increase in stock prices in response, say, to an increase in leverage may result in a positive abnormal return, while the distance to default will decline.

Table 6.8

Monte Carlo Simulations of co-exceedances of weekly logdifferenced distance to default for EU banks, cross country evidence

Reported are the mean numbers of co-exceedances under the different distributional assumptions, given the actual covariance matrix. In parenthesis the number of banks in each country simulated. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances means that many banks in one country can be in the tail simultaneously. The number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
ES-UK (7,7)	*5*	*1*	*6*	*10*	*30*	-	*576*	*581*	-	*24*	*11*	*5*	*7*	*0*
Normal	**0.22**	**0.72**	**2.92**	11.95	**34.72**		577.47	580.29		**32.48**	**11.48**	**2.84**	**0.67**	**0.23**
Student t(5)	9.80	7.32	11.21	16.21	20.35		**563.11**	**563.45**		20.25	**16.05**	11.17	7.33	9.76
Student t (10)	6.40	5.92	10.21	16.35	22.71		566.42	**566.23**		22.89	**16.35**	10.09	6.00	6.45
ES-DE (7,8)	*10*	*6*	*9*	*8*	*7*	-	*498*	*494*	-	*11*	*10*	*9*	*4*	*10*
Normal	**1.80**	**2.14**	**4.79**	12.96	**34.54**		**481.78**	**482.45**		**34.41**	13.03	**4.48**	2.01	**1.63**
Student t(5)	13.04	6.63	9.17	12.63	**15.50**		**481.04**	**480.75**		15.78	12.65	9.07	6.65	13.10
Student t (10)	9.76	5.96	8.96	13.02	**17.55**		**482.75**	**482.51**		17.68	13.11	8.80	6.06	9.86
ES-FR (7,3)	*3*	*3*	*4*	*5*	*7*	-	*408*	*412*	-	*7*	*2*	*4*	*2*	*3*
Normal	**0.14**	**0.33**	**0.77**	**1.50**	**2.50**		**424.76**	**426.48**		**1.84**	0.94	**0.52**	**0.17**	**0.06**
Student t(5)	2.86	3.18	5.28	7.53	9.17		401.98	**402.12**		9.16	**7.48**	5.24	3.18	2.82
Student t (10)	1.77	2.56	4.63	7.45	9.70		403.89	**403.72**		9.94	**7.44**	4.64	2.48	1.77
ES-IT (7,10)	*8*	*2*	*4*	*18*	*24*		*520*	*512*		*24*	*12*	*8*	*9*	*11*
Normal	**0.63**	1.58	5.48	19.35	**50.26**		**498.71**	**498.78**		**50.59**	**19.17**	5.46	**1.45**	**0.55**
Student t(5)	**13.60**	**8.27**	**12.27**	17.43	21.46		**502.97**	**502.67**		21.51	17.71	12.51	8.18	13.41
Student t (10)	8.97	**7.17**	**11.81**	18.45	24.72		**504.88**	504.68		24.65	18.80	11.78	7.25	8.84
DE-UK (8,7)	*9*	*2*	*9*	*6*	*8*		*504*	*489*		*16*	*14*	*9*	*6*	*4*
Normal	**2.20**	2.49	4.83	**12.39**	**25.77**		**490.32**	492.15		**24.45**	11.58	4.99	**2.53**	2.31
Student t(5)	11.54	**6.33**	8.45	11.42	14.37		**485.89**	486.29		14.27	11.41	8.30	6.01	**11.74**
Student t (10)	8.25	5.40	8.01	**11.83**	**15.76**		**488.76**	488.56		16.05	11.72	8.03	5.33	**8.31**

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Table 6.8 - *continued*

Monte Carlo Simulations of co-exceedances of weekly logdifferenced distance to default for EU banks, cross country evidence

DE-FR (8,3)	*5*	*2*	*2*	*4*	*5*	*384*	*380*	*9*	*5*	*2*	*5*	*1*
Normal	**0.29**	**0.35**	0.71	1.42	2.12	**397.11**	**396.04**	**2.87**	**1.66**	0.82	**0.37**	0.26
Student t(5)	3.72	2.74	4.27	6.35	8.03	**376.90**	376.76	8.12	6.40	4.31	2.77	3.63
Student t (10)	2.48	2.29	3.76	6.21	8.54	378.71	378.76	8.58	6.09	3.77	2.31	2.49
DE-IT (8,10)	*10*	*3*	*8*	*9*	*15*	*493*	*483*	*22*	*12*	*5*	*5*	*11*
Normal	**3.95**	3.86	7.95	**17.51**	**34.30**	**470.44**	**470.76**	**33.71**	17.89	7.93	3.87	3.84
Student t(5)	**16.63**	**7.60**	10.26	13.85	16.25	**473.41**	**473.57**	16.17	13.76	10.21	7.68	**16.61**
Student t (10)	12.61	7.03	10.07	14.59	18.89	**474.83**	474.64	18.85	14.95	10.16	7.12	12.28
FR-UK (3,7)	*4*	*1*	*4*	*3*	*4*	*414*	*410*	*7*	*7*	*3*	*2*	*1*
Normal	**0.27**	0.67	1.88	4.65	7.44	415.09	**416.08**	7.33	4.13	1.63	0.59	0.26
Student t(5)	2.88	2.82	4.62	7.21	8.51	**403.96**	403.91	8.67	7.03	4.65	2.82	2.91
Student t (10)	1.74	2.14	4.14	6.95	8.99	**406.04**	405.94	9.10	6.92	4.13	2.22	1.70
FR-IT (3,10)	*5*	*1*	*4*	*6*	*6*	*408*	*406*	*11*	*1*	*3*	*4*	*5*
Normal	**0.23**	0.39	**0.82**	**1.89**	2.93	**423.74**	**414.94**	**2.53**	1.44	**0.62**	**0.27**	**0.20**
Student t(5)	4.78	3.33	5.11	7.42	8.86	**400.49**	400.73	8.69	**7.43**	5.01	3.48	4.67
Student t (10)	2.92	2.68	4.52	7.61	9.88	402.40	402.56	9.63	**7.62**	4.58	2.69	2.92
UK-IT (7,10)	*10*	*3*	*6*	*12*	*19*	*526*	*522*	*22*	*7*	*11*	*5*	*9*
Normal	**1.22**	2.30	6.28	17.00	**34.04**	**515.16**	517.70	**32.33**	**16.26**	**6.23**	2.26	**1.23**
Student t(5)	14.26	**8.31**	**12.15**	16.80	20.32	**504.17**	**504.17**	20.41	**16.91**	12.17	8.29	**14.05**
Student t (10)	9.76	7.34	11.83	18.18	23.50	**505.40**	**505.83**	23.42	**18.08**	11.66	7.51	9.50

Table 6.8a

Monte Carlo Simulations of co-exceedances of weekly first differenced distance to defaults for EU banks, cross–country evidence

Reported are the mean numbers of co-exceedances under the different distributional assumptions, given the actual covariance matrix. In parenthesis the number of banks in each country simulated. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances means that many banks in one country can be in the tail simultaneously. The number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
ES-UK (7,7)	*5*	*1*	*6*	*10*	*30*	-	*576*	*581*	-	*24*	*11*	*5*	*7*	*0*
Normal	**0.01**	0.13	**1.42**	11.59	**46.36**		568.50	**570.61**		**44.42**	11.36	**1.46**	**0.13**	0.02
Student t(5)	8.88	**7.12**	11.07	**16.73**	21.88		**562.31**	**562.03**		22.00	16.95	**11.18**	6.96	**8.88**
Student t (10)	5.40	**5.63**	9.93	**16.79**	24.65		**565.60**	**565.62**		24.55	16.98	10.01	5.56	**5.28**
ES-DE (7,8)	*7*	*2*	*14*	*6*	*12*	-	*497*	*492*	-	*17*	*9*	*6*	*7*	*7*
Normal	**1.96**	2.59	**5.19**	**11.80**	**28.39**		488.08	487.29		**30.25**	11.70	4.85	**2.35**	**1.56**
Student t(5)	**12.52**	**6.38**	8.78	**12.39**	15.53		**482.41**	**482.67**		15.61	12.16	8.79	6.29	**12.47**
Student t (10)	9.36	5.69	**8.44**	**12.27**	17.52		**484.73**	484.86		17.34	12.55	8.32	5.66	9.27
ES-FR (7,3)	*2*	*1*	*1*	*3*	*14*	-	*409*	*420*	-	*5*	*2*	*1*	*0*	*2*
Normal	**0.00**	**0.00**	**0.01**	**0.04**	**0.19**		**429.76**	**429.69**		**0.24**	**0.06**	**0.01**	0.00	**0.00**
Student t(5)	2.04	2.69	**4.84**	**7.62**	9.96		**402.84**	**402.91**		10.01	**7.62**	**4.82**	2.59	2.04
Student t (10)	1.14	1.98	4.13	7.38	10.43		404.94	**405.17**		**10.44**	**7.28**	4.08	1.90	1.13
ES-IT (7,10)	*5*	*2*	*11*	*19*	*25*	-	*514*	*507*	-	*32*	*17*	*5*	*7*	*8*
Normal	**0.02**	**0.21**	**2.47**	17.95	**59.05**		**496.32**	**495.98**		**59.14**	18.18	2.48	**0.21**	**0.01**
Student t(5)	**12.48**	**8.19**	12.52	18.44	22.91		**501.46**	501.16		**22.98**	18.47	**12.80**	8.01	12.58
Student t (10)	7.95	**6.63**	11.82	19.29	26.55		**503.78**	503.36		26.51	19.43	**11.87**	6.98	7.85
DE-UK (8,7)	*6*	*4*	*5*	*11*	*11*	-	*501*	*489*	-	*22*	*13*	*7*	*4*	*3*
Normal	**2.10**	2.58	5.05	11.07	**24.70**		492.50	495.30		22.93	10.47	4.72	2.44	2.14
Student t(5)	**11.05**	5.80	7.97	11.00	13.84		**488.34**	488.48		**13.94**	10.93	7.89	5.86	**10.91**
Student t (10)	7.64	5.07	7.35	11.02	15.42		**491.49**	491.32		15.54	10.95	7.51	4.98	**7.71**

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Table 6.8a - *continued*

Monte Carlo Simulations of co-exceedances of weekly first differenced distance to defaults for EU banks, cross–country evidence

DE-FR (8,3)	*4*	*1*	*3*	*2*	*3*	-	*389*	*387*	-	*7*	*5*	*3*	*0*	*0*
Normal	**0.02**	**0.02**	**0.08**	**0.20**	**0.51**		**401.17**	**400.60**		**0.94**	**0.33**	**0.09**	0.03	0.02
Student t(5)	2.84	2.44	4.06	**6.35**	**8.45**		**377.86**	**377.91**		8.34	6.38	4.09	2.44	**2.84**
Student t (10)	1.65	1.90	3.42	5.98	**8.83**		**380.23**	**380.01**		9.02	5.97	3.44	1.89	1.68
DE-IT (8,10)	*9*	*2*	*7*	*12*	*11*	-	*497*	*483*	-	*23*	*9*	*12*	*4*	*7*
Normal	**2.03**	2.95	6.79	16.43	**33.21**		**476.59**	474.68		**34.61**	**17.00**	**6.84**	2.92	**1.96**
Student t(5)	**16.04**	**7.33**	9.86	13.18	15.59		**476.00**	475.94		15.78	12.94	9.99	7.18	**16.16**
Student t (10)	11.86	**6.69**	9.62	13.85	18.28		**477.71**	478.00		18.13	13.75	9.42	6.77	**11.93**
FR-UK (3,7)	*3*	*1*	*1*	*1*	*9*	-	*415*	*408*	-	*11*	*9*	*2*	*0*	*0*
Normal	**0.01**	0.06	0.34	1.64	**4.45**		**423.50**	**422.64**		**5.16**	**1.76**	**0.38**	0.05	0.01
Student t(5)	2.16	2.47	4.34	**7.18**	8.93		**404.92**	404.86		8.98	7.14	4.38	2.48	2.15
Student t (10)	1.12	1.74	3.65	**6.71**	9.68		**407.09**	407.34		9.57	6.66	3.50	1.73	1.21
FR-IT (3,10)	*4*	*0*	*4*	*4*	*11*	-	*407*	*410*	-	*8*	*3*	*3*	*3*	*3*
Normal	**0.00**	0.00	**0.02**	**0.10**	**0.31**		**429.57**	**429.50**		**0.36**	**0.11**	**0.02**	**0.00**	**0.00**
Student t(5)	4.26	**3.14**	5.16	7.79	9.42		400.23	**400.78**		9.36	7.47	5.17	3.10	4.12
Student t (10)	2.45	2.42	4.40	7.68	10.42		402.64	**402.75**		10.27	**7.64**	4.44	2.44	2.46
UK-IT (7,10)	*6*	*4*	*8*	*15*	*29*	-	*514*	*514*	-	*27*	*22*	*5*	*4*	*4*
Normal	**0.03**	**0.27**	**2.82**	15.93	**42.28**		514.67	520.01		**38.03**	**14.87**	2.76	**0.29**	**0.04**
Student t(5)	**12.84**	8.12	12.08	17.45	**20.98**		**504.54**	**504.56**		21.12	17.21	**12.18**	8.07	**12.87**
Student t (10)	8.28	6.99	11.44	18.24	24.63		506.43	506.67		24.55	18.26	**11.53**	6.88	8.11

Table 6.8b

Monte Carlo Simulations of co-exceedances of weekly abnormal returns for EU banks, cross–country evidence

Reported are the mean numbers of co-exceedances under the different distributional assumptions, given the actual covariance matrix. In parenthesis the number of banks in each country simulated. Co-exceedances are defined such that at least one bank from each country is in the tail. Hence zero co-exceedances means that many banks in one country can be in the tail simultaneously. The number of observations may differ across country groups, as they are determined by the bank with the least number of observations available. Only concurrent samples for banks were used. Figures in bold denote that equality can be rejected at the 5 percent confidence level.

	Number of (co-) exceedances in the bottom tails							Number of (co-) exceedances in the top tails						
	>6	5	4	3	2	1	0	0	1	2	3	4	5	>6
ES-UK (7,7)	*5*	*1*	*6*	*10*	*30*	-	*576*	*581*	-	*24*	*11*	*5*	*7*	*0*
Normal	**0.18**	**0.83**	3.74	14.03	**36.38**		625.84	**625.55**		**36.64**	14.17	**3.71**	**0.78**	0.17
Student t(5)	5.31	6.48	**12.39**	21.57	28.51		**606.74**	**606.76**		**28.58**	21.45	12.31	6.62	**5.29**
Student t (10)	2.16	4.09	9.83	20.42	**32.51**		**611.99**	**611.68**		**32.73**	20.66	9.80	3.94	2.19
ES-DE (7,8)	*5*	*5*	*5*	*16*	*19*	-	*540*	*542*	-	*18*	*18*	*7*	*1*	*4*
Normal	**0.29**	**1.17**	4.74	16.21	**37.77**		**529.83**	**529.82**		**37.83**	16.14	4.70	1.17	**0.35**
Student t(5)	6.49	6.57	**11.52**	18.86	24.74		**521.83**	**522.32**		24.26	18.86	11.50	**6.59**	6.48
Student t (10)	3.03	4.33	9.57	18.69	**28.02**		**526.37**	**526.21**		**27.99**	18.74	9.57	4.50	3.01
ES-FR (7,3)	*2*	*2*	*2*	*9*	*10*	-	*458*	*457*	-	*11*	*11*	*3*	*1*	*0*
Normal	**0.03**	**0.21**	1.46	6.85	**17.41**		457.04	457.79		16.79	6.79	1.44	0.19	0.02
Student t(5)	1.11	2.00	4.67	9.28	12.45		453.49	455.39		11.58	8.40	4.52	2.02	1.09
Student t (10)	0.47	1.12	3.38	8.09	13.26		456.69	458.50		12.09	7.76	3.17	1.05	0.42
ES-IT (7,10)	*7*	*2*	*8*	*19*	*26*	-	*619*	*622*	-	*30*	*14*	*7*	*5*	*3*
Normal	**0.42**	1.52	5.77	18.41	**41.15**		613.73	614.05		**40.83**	18.29	5.84	**1.52**	**0.48**
Student t(5)	10.22	**8.65**	**14.62**	22.67	28.19		**596.66**	**596.72**		27.88	**22.63**	**14.75**	8.70	**10.33**
Student t (10)	4.94	**6.08**	12.40	23.05	33.24		**601.29**	**601.19**		33.54	**22.69**	12.41	6.18	4.98
DE-UK (8,7)	*4*	*9*	*9*	*15*	*36*		*517*	*535*	-	*25*	*15*	*8*	*4*	*3*
Normal	**0.56**	**1.68**	5.61	16.34	33.62		**532.19**	532.60		33.18	16.30	5.61	1.75	**0.57**
Student t(5)	7.16	6.82	11.88	18.71	**23.91**		521.52	**521.68**		23.42	18.93	11.93	6.79	7.25
Student t (10)	3.73	**4.92**	10.00	18.59	27.60		525.17	**525.20**		27.23	18.82	10.07	4.99	3.68

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Table 6.8b - *continued*

Monte Carlo Simulations of co-exceedances of weekly abnormal returns for EU banks, cross–country evidence

DE-FR (8,3)	*1*	*2*	*3*	*9*	*10*	-	*430*	*425*	-	*10*	*12*	*4*	*2*	*2*
Normal	0.23	0.73	2.51	7.67	15.49		428.37	427.99		15.44	7.92	2.59	0.82	**0.25**
Student t(5)	2.34	2.75	5.13	8.74	11.41		424.64	423.86		11.44	8.94	5.41	2.94	2.40
Student t (10)	1.20	1.92	4.12	8.05	12.50		427.21	426.55		12.32	8.43	4.45	2.01	1.24
DE-IT (8,10)	*10*	*2*	*3*	*21*	*27*	-	*527*	*531*	-	*28*	*12*	*5*	*6*	*8*
Normal	**1.05**	2.85	**7.61**	20.01	**37.15**		521.71	520.70		**37.75**	**19.96**	7.88	**2.66**	**1.06**
Student t(5)	12.25	**8.68**	**13.44**	19.48	23.43		**512.71**	**512.25**		23.76	**19.68**	**13.67**	8.68	11.96
Student t (10)	6.58	**6.92**	**12.35**	20.74	28.05		**515.37**	515.01		28.10	**20.80**	**12.56**	6.83	6.70
FR-UK (3,7)	*2*	*1*	*2*	*7*	*9*	-	*462*	*460*	-	*11*	*5*	*2*	*5*	*0*
Normal	**0.10**	0.45	1.85	5.95	12.26		462.39	462.58		12.09	5.93	1.85	**0.45**	0.10
Student t(5)	1.48	2.36	4.95	9.11	12.27		**452.82**	**452.95**		12.01	9.14	5.03	2.35	1.54
Student t (10)	0.67	1.42	3.70	8.18	13.39		455.63	456.03		12.79	8.28	3.74	**1.45**	0.71
FR-IT (3,10)	*4*	*1*	*2*	*6*	*8*	-	*462*	*459*	-	*4*	*12*	*2*	*3*	*3*
Normal	**0.38**	0.95	3.04	7.76	14.00		456.88	457.62		**13.37**	7.81	2.95	0.90	**0.36**
Student t(5)	3.72	3.40	5.76	9.02	11.24		**449.85**	451.76		**10.54**	8.51	5.32	3.26	3.61
Student t (10)	1.93	2.32	4.82	9.04	12.75		**452.15**	455.25		**11.25**	8.02	4.36	2.25	1.87
UK-IT (7,10)	*9*	*8*	*6*	*21*	*28*	-	*609*	*611*	-	*41*	*13*	*4*	*5*	*7*
Normal	**0.96**	**2.73**	8.76	23.82	**43.43**		601.29	601.33		43.54	**23.57**	8.76	2.84	**0.96**
Student t(5)	11.59	9.22	**14.78**	22.22	27.50		**595.69**	**595.78**		**27.41**	**22.68**	**14.69**	9.20	11.23
Student t (10)	5.95	6.76	**13.21**	23.53	32.25		599.30	**599.73**		32.32	**22.96**	**13.02**	6.90	6.06

also below, we view this as a major caveat and would place greater emphasis on results obtained using the distance to default as a measure of bank risk.[79]

We reach similar conclusions when considering cross-country co-exceedances. The results for the log-differenced distance to default, the first differenced distance to default and abnormal returns are reported in Tables 6.8, 6.8a and 6.8b, respectively. We performed exactly the same exercise, simulating multivariate Normal and student t distributions with 5 and 10 degrees of freedom, using the historical variance-covariance matrix to replicate the patterns of co-exceedances reported in Table 6.5. In case of the log-differenced distance to default (Table 6.8), neither the multivariate Normal nor the student t distributions can replicate the patterns of co-exceedances observed in the data for any country pair, except for Germany-France. In all cases (aside from Germany-France) we can reject equality based on the 5 percent simulated confidence band at least for some level of co-exceedances. This is true for the bottom as well as for the top tail co-exceedances. Again, patterns are strikingly similar for the first differenced distance to default (Table 6.8a), although in this case there is rejection in all cases. Finally, for the abnormal returns (Table 6.8b), we find that we cannot reject that the simulated patterns coincide with actual patterns for two country pairs: Germany-France and France-Spain. Nevertheless, the difference for the cross-border co-exceedances between the three measures seem even smaller than in the case of within country co-exceedances and the inability of the simulations to replicate the patterns observed in the data even more striking.

Table 6.9 gives some summery statistics for the Monte Carlo Simulations. Overall, the normal distribution is unable to explain the patterns in the data. There is virtually no country or country pair, in which there is not at least one rejection. The student t distributions, especially the student t with 10 degrees of freedom, do slightly better, but for all measures there are only few countries or country pairs, for which there is not at least one rejection. While our simulation difficulties may ultimately concern only a relatively small number of observations, the events that occur "too often" compared to multivariate Normal or student t distributions may be precisely those one would be interested in from the perspective of bank contagion.

6.4.2 Differences in conditional sample frequencies: A measure of net contagious influence

Given this evidence in favor of non-linearities in the tail of the distribution, there are a number of avenues for how to proceed. Bae, Karolyi and Stulz (2003) propose a multi-nomial logistic regression model, utilizing the fact that the co-presence of observations

[79] We also examined the sensitivity of the results to the choice of the size of the tail. While all calculations in the paper were performed for 5 percent tails, we redid the analysis for 10 percent tails and found virtually identical results for the difference in the distance to default. The results are available upon request.

Table 6.9
Summary statistics for Monte Carlo simulations

	Log-differenced distance to default	First differenced distance to default	Abnormal returns
Within country			
% rejections			
Bottom tails (total 45)			
Multivariate normal	62.2%	73.3%	55.5%
Student t (5)	28.9%	24.4%	13.3%
Student t (10)	26.7%	20.0%	15.6%
Top tails (total 45)			
Multivariate normal	57.7%	62.2%	44.4%
Student t (5)	17.8%	17.8%	31.1%
Student t (10)	13.3%	15.6%	13.3%
No rejection: # of countries (total 8)			
Bottom tails			
Multivariate normal	0	0	1
Student t (5)	3	4	6
Student t (10)	3	3	5
Top tails			
Multivariate normal	1	1	2
Student t (5)	3	4	3
Student t (10)	5	4	5
Both tails			
Multivariate normal	0	0	0
Student t (5)	1	3	3
Student t (10)	1	1	5
Across country pairs			
% rejections			
Bottom tails (total 60)			
Multivariate normal	61.7%	63.4%	36.7%
Student t (5)	30.0%	43.3%	25.0%
Student t (10)	18.3%	25.0%	20.0%
Top tails (total 60)			
Multivariate normal	61.7%	63.4%	35.0%
Student t (5)	21.7%	30.0%	30.0%
Student t (10)	15.0%	20.0%	23.3%
No rejection: # of country pairs (total 10)			
Bottom tails			
Multivariate normal	0	0	1
Student t (5)	1	0	2
Student t (10)	4	3	3
Top tails			
Multivariate normal	0	1	1
Student t (5)	2	2	2
Student t (10)	4	3	2
Both tails			
Multivariate normal	0	0	0
Student t (5)	0	0	2
Student t (10)	1	0	2

in the tails can be modeled as a polychotomous variable. Alternatively, GARCH-M models, modeling changing volatilities asymmetrically, may also be a way forward (see e.g. Ang and Chen, 2002). We follow a different approach, refraining from making any assumptions about the underlying data generating process. Instead we propose the following simple non-parametric measure of net contagious influence of bank A on bank B

$$\Omega_{A/B} = P(B_T / A_T) - P(A_T / B_T) \qquad \textbf{(6.6)}$$

where $P(B_T / A_T)$ denotes probability that bank B is in the tail of the distribution in some period given that bank A is also in the tail. Expression (6.6) is simply the difference in the observed conditional sample frequencies of bank A and bank B experiencing a tail event. Under which circumstances does (6.6) give us an accurate signal regarding the net contagious influence between the two banks? Assume that all shocks are i.i.d. over time. Suppose further that idiosyncratic shocks and the macro shock are jointly distributed. In addition, we need to define some notation:

(i) I_S represents the realization of bank I's idiosyncratic shock, where $I \in$ (A,B).
(ii) I_T represents the event that bank I is in the tail of the distribution.
(iii) M is the realization of the common shock. A common shock is defined such that upon its realization both banks are in the tail.
(iv) p_{AB} represents the probability that there is contagious influence from bank A to bank B. We define contagious influence such that bank B is not hit by a shock (either common or idiosyncratic) but is in the tail and A is hit by an idiosyncratic shock, which through contagious influence results in bank B experiencing a tail event.

We claim that there is net contagious influence from bank A to bank B if $p_{AB}>p_{BA}$. Recall that for any two banks A and B, bank A can be in the tail of the distribution if

(i) it is hit by an idiosyncratic shock (A_S) and B is or is not hit by an idiosyncratic shock, or
(ii) if there is a common (macro) shock (M) affecting both banks simultaneously, or
(iii) if bank B is hit by an idiosyncratic shock and there is contagion from bank B to bank A.

We do not assume that the system of the two banks A and B is closed. This means that we do not exclude the possibility of outside contagion. However, if this outside contagion affects either bank individually, this is observationally equivalent to an idiosyncratic shock affecting the bank and, hence, is subsumed under I_S. Similarly, suppose both banks experience contagion from some bank other than A and B. In our framework this would be subsumed under the banks experiencing a common shock. Note that the phrase common shock, as used here, is distinct from a macro shock affecting all banks; rather a common shock is simply a shock affecting both banks, such that they are in the tail of the distance to default or abnormal return distribution. This can, but must not be, a macro shock.

Breaking down the conditional probabilities of being in the tail into their components we obtain (where ¬ denotes 'not'):

$$p(B_T \mid A_T) = \frac{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M)p_{AB} + pr(\neg A_S, B_S, \neg M)p_{BA} + pr(M)}{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M) + pr(\neg A_S, B_S, \neg M)p_{BA} + pr(M)} \quad \textbf{(6.7)}$$

$$p(A_T \mid B_T) = \frac{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M)p_{AB} + pr(\neg A_S, B_S, \neg M)p_{BA} + pr(M)}{pr(A_S, B_S, \neg M) + pr(A_S, \neg B_S, \neg M)p_{AB} + pr(\neg A_S, B_S, \neg M) + pr(M)} \quad \textbf{(6.8)}$$

A necessary condition for these probabilities to be defined is that the denominator of the two expressions does not become zero. For this we need that each bank has some non-zero probability of experiencing an idiosyncratic shock or that there exists some common shock.

Further, given the decomposition, we immediately see that $p(B_T|A_T)-p(A_T|B_T)>0$ is equivalent to

$$\frac{(1-p_{BA})}{(1-p_{AB})} - \frac{pr(A_S, \neg B_S, \neg M)}{pr(\neg A_S, B_S, \neg M)} > 0 \quad \textbf{(6.9)}$$

Condition (6.9) gives some idea about when the measure of contagious influence gives an accurate signal. The accuracy of the signal is inversely related to the ratio of the probabilities that that bank A or bank B is hit by an idiosyncratic shock. Put differently, if those probabilities are approximately equal, then the measure identifies contagion accurately. Unfortunately, the measure may also understate or overstate true contagion, if the difference in the probability of experiencing an idiosyncratic shock is large. For example, suppose in reality there is no contagion (i.e. $p_{AB}=p_{BA}=0$), but bank B has a much higher probability of experiencing an idiosyncratic shock compared to bank A (i.e. if $pr(\neg A_S, B_S, \neg M) >> pr(A_S, \neg B_S, \neg M)$). Condition (6.9) tells us that in this case, the measure may suggest contagion, even though there is none. Conversely, suppose in reality there is contagion. If bank A is very likely to experience an idiosyncratic shock (i.e. if $pr(\neg A_S, B_S, \neg M) << pr(A_S, \neg B_S, \neg M)$), then the measure tends to understate true contagion.[80]

[80] In fact, given our assumption that the system is "open", $pr(A_s, \neg B_s, \neg M)$ is composed of the probability of being his of an idiosyncratic shock plus the probability of experiencing contagion from some "outside" bank $i \neq B$. Hence, a somewhat less stringent requirement for $\Omega_{A/B}$ to give a correct signal is that the two components be perfectly negatively correlated. If this is violated, holding the probability of experiencing an idiosyncratic shock constant, the measure will understate contagion from banks with a lot of outside contagion to banks with little outside contagion. This means that the measure understates contagion from banks, which themselves experience a lot of contagion to banks which do not and may overstate contagion from banks, which do not experience "outside" contagion to those that do.

Figure 6.2
A Simple Example

Case 1

Panel A

Period	Bank A		Bank B
1	*	→	*
2			*
3			
4			
5			
Pr(x in tail)	0.20		0.40
Pr(A and B in tail)	0.20		0.20
Omega		0.50	

Case 2

Period	Bank A		Bank B
1	*	→	*
2			*
3	*		*
4			
5			
Pr(x in tail)	0.40		0.60
Pr(A and B in tail)	0.40		0.40
Omega		0.33	

Case 3

Period	Bank A		Bank B
1	*	→	*
2			*
3	*	→	*
4			*
5			
Pr(x in tail)	0.40		0.80
Pr(A and B in tail)	0.40		0.40
Omega		0.50	

Case 4

Period	Bank A		Bank B
1	*	←	*
2			*
3	*	→	*
4	*		
5			
Pr(x in tail)	0.60		0.60
Pr(A and B in tail)	0.40		0.40
Omega		0.00	

In order to illustrate the intuition behind equation (6.5) consider the example given in Figure 6.2. In Case 1, there are five periods. In period 1 we observe that both banks are in the tail of the distribution of Δdd and in period 2, we see only bank B in the tail. This means that in period 2 bank B experienced an idiosyncratic shock. If we assume that the probabilities of experiencing an idiosyncratic shock are equal across the two banks then the two banks should have an equal number of realizations of the idiosyncratic shock on average.[81] This means the presence of bank A in the tail in period 1 *must* be the realization of an idiosyncratic shock. In turn this implies that there was contagion from bank A to bank B. Hence, the approach uses the information contained both in the realization of idiosyncratic as well as common shocks. Now consider Case 2. The only change involves period 3, in which both banks again are present in the tail. As before, we

[81] Of course this is not necessarily true over five periods as in this example. In the actual data, there are around 600 periods.

observe that Bank B has a realization of an idiosyncratic shock in period 2. Again, this suggests that bank A must have experienced an idiosyncratic shock either in period 1 or in period 3, which was transmitted through contagion to bank B. Why does $\Omega_{A|B}$ decline from 0.5 in Case 1 to 0.33 in Case 2? The reason is that we have information, which may suggest that the contagious influence from bank A to bank B may be smaller. We know that there is contagion from bank A to bank B either in period 1 or 3. But we do not know what happened in the other period. Suppose there was contagion in period 1. In period 3, there was either the realization of the common shock or each of the banks experienced an idiosyncratic shock. This means that the probability of contagion from A to B may be lower (but must not be lower), hence the lower $\Omega_{A/B}$. In Case 3, bank B experiences one additional realization of the idiosyncratic shock in period 4. Again this provides additional information. Under the assumption that both banks have an equal number of realizations of the idiosyncratic shock, both periods when both banks are in the tail bank A must have experienced an idiosyncratic shock and transmitted it to bank B. In the final Case 4, we cannot distinguish the case of a common shock affecting both banks in periods 1 and 3 from the possibility that in one period bank A transmitting its idiosyncratic shock to bank B and in another the contagion goes the other way. Hence, $\Omega_{A|B}$ shows no "net contagious influence."

This discussion has highlighted that the accuracy of the contagious influence measure proposed depends on the difference between the probabilities of each bank to be hit by an idiosyncratic shock. The example shows that if this probability is not equal, the signal given by $\Omega_{A|B}$ is not informative. This probability of an idiosyncratic shock is unobservable. One solution to this problem may be to attempt to control for the difference between the two probabilities through some bank characteristic, which may be related to the likelihood of experiencing an idiosyncratic shock. The problem is that the variable should also be orthogonal to the likelihood of being subject to contagion. In this chapter, we use the size of the bank as measured in total assets as a candidate variable. We view size as a summary variable of the different business mix of large banks compared to small banks, which in turn tends to expose them to different shocks. For example, large banks may have only very little exposure to the small business sector, while small banks may conduct a majority of their business there. Similarly, large banks exposure to the stock market or to foreign exchange markets may be much larger than the one of small banks.[82] Hence we estimate

$$\Omega_{A/B} = \beta_0 + \beta_1 \left[\frac{S_A}{S_B} \right] + \varepsilon_{A/B} \tag{6.10}$$

[82] Obviously, larger banks may also be better diversified compared to small banks and, hence, less likely to be subject to contagion.

Table 6.10
Results from the estimation of equation (6.10): Adjusted net-contagious influence

*, **, *** denotes significance at the 10, 5 and 1 percent levels, respectively. Coefficients for differences in sample size not reported.

Dependent variable	β_0	β_1	R^2	n
Log-differenced distance to default				
Positive tail	0.01*	0.03***	0.24	2211
	(0.006)	(0.001)		
Negative tail	0.076***	0.023***	0.28	2211
	(0.006)	(0.001)		
Both tails	0.043***	0.028***	0.35	2211
	(0.005)	(0.001)		
Abnormal returns				
Positive tail	0.023***	0.007***	0.02	2211
	(0.007)	(0.002)		
Negative tail	0.024**	0.002	0.01	2211
	(0.009)	(0.002)		
Both tails	0.02**	0.005***	0.01	2211
	(0.002)	(0.002)		

where S_i represents an indicator of the size of bank *i* (see below). We then calculate the "adjusted" measure of net-contagious influence as the residuals of equation (6.10), i.e.

$$\Omega^*_{A/B} = \Omega_{A/B} - \hat{\beta}_1\left[\frac{S_A}{S_B}\right] - \hat{\beta}_0 \qquad \textbf{(6.11)}$$

To calculate S, we assign each bank a quartile ranking for size in each sample year (i.e. a ranking from 1 to 4, with one being "smallest" and four being "largest"). Hence, S_A/S_B can potentially vary from 0.25 to 4. As $\Omega^*_{A/B}$ is a time invariant measure, we use simple averages over the ten-year sample period of the bank characteristics. Put differently, we assign a quartile ranking in each year and then take an average of this ranking. As the dependent variable exists for each bank pair in the sample, with 67 banks, the sample size is 67!/(65!-2!)=2211 observations.

Equation (6.10) is estimated separately for the log-differenced distance to default[83] and the abnormal returns. In addition, we estimate equation (6.10) separately for negative and positive tails, and for both tails. The estimated coefficients are reported in Table 6.10. Before we discuss them, we should clarify that we have no particular prior about the sign of $\hat{\beta}_1$. If size is positively correlated with being exposed to idiosyncratic risk, because larger banks have a greater exposure to volatile asset markets (especially if they take significant unhedged positions), we would see a positive coefficient. If the diversification effect dominates, we should see a negative coefficient. Table 6.10 shows that the estimated is indeed positive and significant at the 1 percent level in 5 of the 6 specifications. Only for negative tails of abnormal returns, we find no significance. Note also, however, that while we explain between 24 and 35 percent of the variation in $\Omega^*_{A/B}$ for log-differenced distances to default, equation (6.10) only explains very little of the variation in $\Omega^*_{A/B}$ for abnormal returns.

Next, we examine the obtained results for $\Omega^*_{A/B}$ for the two measures of bank risk. The Spearman rank correlation coefficient is 0.17 for positive tails, 0.09 for negative tails and 0.16 for both tails. Independence can be rejected at any significance level. While this is encouraging, the correlation coefficients are quite low and it may be instructive to examine whether the method yields consistent signals across the measures of bank risk regarding which banks may be of particular systemic importance. We use the term "systemic importance" here in the sense that banks with systemic importance are banks that tend have net-contagious influence on other banks.

6.5 Systemic banks

6.5.1 Within-country systemic risk

We define a bank i as having systemic importance within-country Y if:

$$\Phi_i^{within} = \sum_{j \in Y} \Omega^*_{i/j} > 0 \qquad \textbf{(6.12)}$$

This simply suggests that if the sum of the net contagious influence of a bank with respect to its peers in the same country is positive, it may have systemic importance for the banking system as a whole. See Table 6.11 for the statistics of the measure. We report results for $\Omega_i^{\text{within}} > 0.1$, in order to eliminate contagious influence that is very close to

[83] We report the results only for the log differences of the distance to default and not the results for the first differences of the distances to default, since we saw in the simulations that both measures yield essentially equivalent patterns of co-exceedances.

Table 6.11
Statistics of the measure $\Omega^*_{i/j}$, Ω_i^{within} and Ω_i^{across}

This table presents the statistics for our measure used. For sake of brevity we only mention the statistics for the both tails simultaneously. The results for the negative and positive tail are similar for each measure.

Variable		Mean	Stand. dev.	Min.	Max.	Obs.	10% tail	5% tail
$\Omega^*_{i/j}$	ln(Δdd)	0.000	0.042	-0.292	0.172	2211	0.047	0.068
$\Omega^*_{i/j}$	abnormal returns	0.000	0.059	-0.303	0.239	2211	0.069	0.097
Ω_i^{within}	ln(Δdd)	0.000	0.309	-0.904	0.877	67	0.322	0.498
Ω_i^{within}	abnormal returns	0.000	0.549	-2.055	1.866	67	1.693	2.101
Ω_i^{across}	ln(Δdd)	0.000	1.488	-5.830	3.741	67	0.491	0.710
Ω_i^{across}	abnormal returns	0.000	2.177	-7.126	5.429	67	2.58	2.94

zero[84]. The results for this exercise are given in Table 6.12. Note that we can only identify systemically important banks in countries, where the sample contains more than one bank and that in countries where the sample only contains two very large banks, we tend to not to be able to detect significant contagious influence.[85] This excludes Belgium and in Austria, Denmark, Finland and Greece we are unable to identify systemically important banks. In the table, we rank banks within countries, i.e. the bank listed first has the largest net-contagious influence within a country. A first result is that there seems to be little difference between considering negative versus positive tails or both tails jointly, but noticeable differences across the two measures of bank risk (log-differenced distance to default and abnormal returns). Contagion, as measured here, appears to be symmetric for negative and positive shocks. This finding will largely carry through to cross-border contagion considered below.

Now consider the banks that one would have expected to have systemic importance judging simply from their size in the country. These banks include Deutsche Bank and HVB (DE), and BBVA (ES). In addition, while not the largest banks in the country, it is no surprise to find National Westminster Bank, and HSBC (both UK) in this group, as well as Sanpaolo IMI, Unicredito (both IT), Svenska Handelsbanken (SE) and ING (NL). These results are largely unaffected whether we consider the log-differenced

[84] The threshold of Ω_i^{within} >0.1 does not imply any claim about significance of the results. Merely, we want to exclude those banks whose contagious influence is very close to zero.
[85] Essentially we need at least some banks that are exposed to contagious influence.

Table 6.12
Within country contagious influence

All banks with $\Omega_i^{within} > 0.1$. Within countries banks are ranked by the size of Ω_i^{within}. Abbreviations used: Banco Popular Espanol (BPE), Banco Guipuzcoano (BG), Credito Valtellinese (CV), Banca Agricola Mantonvana (BAM), Banca Popolare di (BP), Banca Desio e della Brianza (BDB), Banca Popolare Commercio e Industria (BPCI), Banco Espirito Santo (BES), National Westminster (NW).
1/ There is only one bank from Belgium in the sample.

Country	**Log-differenced distance to default**			**Abnormal returns**		
	Positive tail	**Negative tail**	**Both tails**	**Positive tail**	**Negative tail**	**Both tails**
Austria	None	None	None	None	None	None
Belgium	n.a. 1/	n.a. 1/	n.a. 1/	n.a. 1/	n.a. 1/	n.a. 1/
Germany	BHVB Deutsche B Dresdner B	IKB Deutsche B	Deutsche B BHVB Dresdner B	Deutsche B IKB	Deutsche B IKB BHF	Deutsche B IKB BHF
Denmark	None	None	None	None	None	None
Spain	B Zaragozano B Santander BBVA BG	BPE B Pastor	BPE B Zaragozano BG	BG	BG BBVA	BG
Finland	None	None	None	None	None	None
France	BNP Paribas	CPR	BNP Paribas	None	Societe Generale	Societe Generale
Greece	None	None	None	None	None	None
Ireland	None	None	None	B of Ireland	B of Ireland	B of Ireland
Italy	Sanpaolo IMI Unicredito BP Milano BDB Rolo Banca BPCI	Sanpaolo IMI Rolo Banca Banca di Roma BP Intra BP Bergamo BDB	Sanpaolo IMI Rolo Banca Unicredito BP Milano BDB B di Roma BP Bergamo	CV BP Bergamo BDB BPCI BAM Unicredito Sanpaolo IMI B Lombarda Rolo Banca	CV BAM B Lombarda BP Bergamo BPCI BDB Sanpaolo IMI Rolo Banca BP Intra	CV BP Bergamo BAM BDB BPCI B Lombarda Sanpaolo IMI Rolo Banca
Netherlands	ING	None	ING	None	ING	None
Portugal	None	BES BPI	None	BES	BES	BES
Sweden	Handelsbanken	Handelsbanken	Handelsbanken	None	Handelsbanken	Handelsbanken
United Kingdom	NW B of Scotland Abbey National HSBC	NW B of Scotland Abbey National HSBC Stand. Chartered RB of Scotland	NW B of Scotland Abbey National HSBC	NW HSBC	HSBC NW RB of Scotland	HSBC NW

distance to default or abnormal returns. However, there is a number of important exceptions to this consistency. One, using the log-differenced distance to default, we identify Dresdner Bank as systemically important in Germany, BNP Paribas in France and a number of UK banks including Bank of Scotland and Abbey National. Using abnormal returns, we no longer identify these banks and instead IKB (DE), Societe Generale (FR) and Royal Bank of Scotland appear. We explain these inconsistencies across the log-differenced distance to default and abnormal returns by their differences. An increase in stock price volatility associated with an increase in the stock price will result in an unambiguously positive abnormal return, while the effect is ambiguous on the distance to default. This is so because the distance to default is declining in asset price volatility. Hence, the observed differences can very likely be explained by differences in the type of shocks (rather than their frequency) that the banks experienced.

There are a number of additional surprises, mainly relating to Portuguese, Italian and Spanish banks. In Portugal, instead of the largest bank in the country, Banco Comercial Portugues, Banco Espirito Santo is identified, which is considerably smaller. The most surprising findings emerge for Italy and Spain. In Spain, while BBVA and Banco Santander do appear in the table, neither is consistently identified as systemically important, although they are by far the largest banks in Spain. Instead, we identify some of the smallest banks in our sample: Banco Popular Espaniol (1/10 the size of Banco Santander), Banco Guipuzcoano (1/60 of Banco Santander) and Banco Zaragozano (1/60 of Banco Santander). Similarly in Italy, while Sanpaolo IMI is consistently identified and somewhat less consistently Unicredito, Banca Intesa, the largest bank in Italy, does not appear at all. Instead, the method identifies a number of very small banks as having contagious influence within Italy.

What can explain these surprising findings? Recall that the measure employed crucially depends on the equality of the probability of being hit by an idiosyncratic shock. We used differences in size to proxy for this, but it appears from these results that the proxy is insufficient. Hence, below we will also report results limited to the largest banks in the sample.

6.5.2 Across-country systemic banks

Analogously to identifying within country systemically important banks, we can also identify systemically important banks for the sample countries as a whole. We define a bank i as systemically important for banks in country Z if

$$\Phi_i^{across} = \sum_{k \in Z} \Omega_{i/k}^* > 0, \qquad i \in Y, \qquad Z \neq Y \qquad \textbf{(6.13)}$$

Hence, this section attempts to identify banks that can be considered systemically important in the EU as a whole. The results are summarized in Table 6.13, where we –as

Table 6.13
Cross-country contagious influence

Only banks with Ω_i^{across} >0.1 listed. Abbreviations used: Banco Popular Espanol (BPE), Banco Guipuzcoano (BG), Credito Valtellinese (CV), Banca Agricola Mantovana (BAM), Banca Popolare di (BP), Banca Desio e della Brianza (BDB), Banca Popolare Commercio e Industria (BPCI), Banco Espirito Santo (BES), Banco Totta e Acores (BTA), Banco Commercial Portugues (BCP), National Westminster (NW).

Country	Log-differenced distance to default			Abnormal returns		
	Positive tail	Negative tail	Both tails	Positive tail	Negative tail	Both tails
Austria	None	Creditanstalt	None	None	Bank Austria	None
Belgium	None	None	None	KBC	KBC	KBC
Germany	Deutsche B BHBV Dresdner B IKB	IKB Deutsche B	Deutsche B IKB BHBV Dresdner B	Deutsche B IKB BHF Dresdner B	Deutsche B IKB BHF Dresdner B Commerzbank	Deutsche B IKB BHF Dresdner B Commerzbank
Denmark	Danske Bank Jyske Bank	Jyske Bank Danske Bank	Jyske Bank Danske Bank	Danske Bank Jyske Bank	Danske Bank Jyske Bank	Danske Bank Jyske Bank
Spain	BG B Zaragozano	BPE B Pastor B Zaragozano BG	BPE B Pastor B Zaragozano BG	BG BBVA BPE B Santander B Zaragozano B Pastor	BBVA BG B Pastor BPE B Santander B Zaragozano	BBVA BG B Pastor BPE B Santander B Zaragozano
Finland	Okobank	Okobank Sampo Leonia	Okobank	None	None	None
France	BNP Paribas CPR Natexis BP	CPR Natexis BP	CPR Natexis BP BNP Paribas	None	None	None
Greece	None	Alpha Bank	None	Alpha Bank	None	Alpha Bank
Ireland	Allied Irish B Anglo Irish B B of Ireland	Allied Irish B Anglo Irish B B of Ireland	Allied Irish B Anglo Irish B B of Ireland	Allied Irish B B of Ireland	Allied Irish B B of Ireland	Allied Irish B B of Ireland
Italy	BP Milano Sanpaolo IMI Unicredito BAM	Rolo Banca Sanpaolo IMI B di Roma	Sanpaolo IMI BP Milano Rolo Banca CV	CV BAM BP Bergamo BPCI BDB B Lombarda	CV BAM B Lombarda BP Bergamo BDB BP Intra	CV BAM B Lombarda BP Bergamo BDB BP Intra
Netherlands	ING Kas Assoc. ABN Amro	None	ING	ING ABN Amro	ING ABN Amro Kas Assoc.	ING ABN Amro
Portugal	None	BPI BES	BPI	BCP BES BPI BTA	BCP BES BPI BTA	BCP BES BPI BTA
Sweden	Handelsbanken	Handelsbanken	Handelsbanken	None	None	None
United Kingdom	Abbey National B of Scotland NW HSBC RB of Scotland Barclays Stand. Chartered	Abbey National RB of Scotland NW Barclays Stand. Chartered HSBC B of Scotland	Abbey National HSBC Barclays B of Scotland RB of Scotland NW Stand. Chartered	NW HSBC	NW HSBC	HSBC NW

before- only report the banks with $\Omega_i^{\text{across}} > 0.1$.[86] Let us start with the expected. Deutsche Bank (#1 by total assets), Dresdner Bank (#6), ABN Amro (#4), ING (#9), National Westminster Bank (#12), Danske Bank (#19) and HSBC (#15) are all consistently identified as systemically important for the banks in the sample outside of their own country. In addition, there is evidence that HBV (#2), BNP Paribas (#3), Banco Santander (#10) and BBVA (#14) have some systemic importance, but the evidence is less clear. On the other hand, we have surprises among the included as well as the omitted banks. Among the included banks, we find IKB (DE, #42), Allied Irish Banks (#30) and Bank of Ireland (#31, both IE), BPI (PT, #49) and some very small Spanish and Italian banks to have contagious influence. The notable omissions include Barclays (UK, #5), Societe Generale (FR, #7) and Banca Intesa (IT, #11).

In order to ascertain to which extent this is due to insufficiently controlling for the likelihood of idiosyncratic shocks, we redid the analysis, considering only banks above EUR 50 billion in total assets (the 33 largest banks of the sample, see Table 6.2). The idea is that these banks may be more similar in terms of their probability of experiencing an idiosyncratic shock. This exercise also addresses the question of how sensitive the results are to the sample composition, i.e. whether or not a specific bank is included. In addition, of course, the limitation gives an idea of contagion among the largest banks only, which may be of independent interest. Table 6.14 shows that the results are quite robust. By definition, the smallest banks no longer appear in the table, but those that do appear tend to be identical to those when using the full sample.

The approach summarized here, which consists of unweighted sums, may hide considerable bilateral links among banks. For example, a bank would be found not to have any contagious influence based on Ω_i^{within} and Ω_i^{across}, if it had a strong contagious influence on one bank, but was subject to an equally strong contagious influence from another bank. In order to address this issue, we prepared Table 6.15, which lists the number of banks that have contagious influence on at least three other banks. We are considering “strong” contagious influence only; that is the upper 10 percent tail of the distribution of $\Omega^*_{A/B}$. We report the results for cross-border contagion only. Comparing these results to those in Table 6.13, the main finding is that there is somewhat more consistency across the rows of the table. Fundamentally, however, Tables 6.13 and 6.15 exhibit surprising consistency.

[86] The list of banks would have been longer, of course, if we had reported all banks with $\Omega_i^{\text{across}} > 0$ (for the statistics on this measure, see Table 11). While we do not make any claims about statistical significance, by using this nonzero threshold, we exclude banks whose contagious influence is essentially zero. Note that the number of banks differs somewhat, as banks in the same country do not enter Ω_i^{across}. Hence for KBC the sum $\Sigma_{k \in Z}\, \Omega_i^{\text{across}}$ contains 66 items (KBC is the only Belgian bank in the sample), while for Italian banks it contains 50 items, i.e. 67 total – 17 Italian banks. It is clear that even banks with small or even negative Ω_i^{across} may exercise some net contagious influence on <u>some</u> banks. We will examine this in more detail below.

Table 6.14
Cross country contagious influence:
Banks with total assets of EUR 50 billion or more

Only banks with Ω_i^{across} >0.1 listed. Abbreviations used: Banco Comercial Portugues (BCP) and National Westminster (NW).

Country	Log-differenced distance to default			Abnormal returns		
	Positive tail	Negative tail	Both tails	Positive tail	Negative tail	Both tails
Austria (1)	None	None	None	None	Bank Austria	None
Belgium (1)	None	None	None	KBC	KBC	KBC
Germany (7)	Deutsche B Dresdner B BHBV	Deutsche B	Deutsche B BHBV Dresdner B	Deutsche B Dresdner B BHF	Deutsche B Dresdner B BHF Commerzbank	Deutsche B Dresdner B BHF
Denmark (1)	Danske Bank	Danske Bank	Danske Bank	Danske Bank	Danske Bank	Danske Bank
Spain (2)	None	None	None	BBVA B Santander	BBVA B Santander	BBVA B Santander
Finland (-)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
France (3)	BNP Paribas Natexis BP	Natexis BP	Natexis BP BNP Paribas	None	None	None
Greece (-)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Ireland (2)	Allied Irish B B of Ireland	Allied Irish B B of Ireland	Allied Irish B B of Ireland	Allied Irish B B of Ireland	Allied Irish B B of Ireland	Allied Irish B B of Ireland
Italy (4)	Sanpaolo IMI Unicredito	Sanpaolo IMI Banca di Roma	Sanpaolo IMI	None	None	None
Netherlands (2)	ING ABN Amro	None	ING	ING ABN Amro	ING ABN Amro	ING ABN Amro
Portugal (1)	None	None	None	BCP	BCP	BCP
Sweden (2)	Handelsbanken	None	Handelsbanken	None	None	None
United Kingdom (7)	Abbey National B of Scotland Barclays HSBC NW RB of Scotland	Abbey National B of Scotland Barclays HSBC NW RB of Scotland Stand. Chartered	Abbey National B of Scotland Barclays HSBC NW RB of Scotland Stand. Chartered	HSBC NW	HSBC NW	HSBC NW

Table 6.15
Cross country contagious influence

In parenthesis: Number of banks on which bank exercises "strong" contagious influence. "Strong" is defined as the upper 10 percent tail of $\Omega^{*}_{A/B}$. Only banks with contagious influence to at least three other banks are reported. Banco Popular Espanol (BPE), Banco Guipuzcoano (BG), Credito Valtellinese (CV), Banca Agricola Mantonvana (BAM), Banca Popolare di (BP), Banca Desio e della Brianza (BDB), Banca Popolare Commercio e Industria (BPCI), Banco Espirito Santo (BES), Banco Comercial Portugues (BCP), National Westminster (NW).

Country	Log-differenced distance to default			Abnormal returns		
	Positive tail	Negative tail	Both tails	Positive tail	Negative tail	Both tails
Austria	None	Creditanstalt (3)	None	None	None	None
Belgium	None	None	None	KBC (10)	None	KBC (4)
Germany	HBV (11) Deutsche B (15) Dresdner B (7)	Deutsche B (4) IKB (6)	HBV (4) Deutsche B (10) Dresdner B (4)	Deutsche B (16) IKB (3)	BHF (3) Commerzbank (6) Deutsche B (10) Dresdner B (4) IKB (10)	BHF (3) Commerzbank (5) Deutsche B (14) Dresdner B (3) IKB (5)
Denmark	None	Jyske Bank (4)	Jyske Bank (3)	Danske Bank (11)	Danske Bank (12) Jyske Bank (9)	Danske Bank (12) Jyske Bank (4)
Spain	BBVA (3) BPE (3) B Santander (3) B Zaragozano (3)	B Pastor (3) BPE (8)	BPE(3)	BBVA (5) BG (6) BPE (5) B Santander (4) B Zaragozano (4)	BBVA (8) B Pastor (3) B Santander (3)	BBVA (9) B Guipuzcoano (4) B Pastor (3) BPE (3) B Santander (3)
Finland	None	Sampo Leonia (7)	None	None	None	None
France	BNP Paribas (12) Natexis BP (3)	None	BNP Paribas (5)	BNP Paribas (3)	None	None
Greece	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Ireland	Allied Irish B (6) Anglo Irish B (3) B of Ireland (4)	Allied Irish B (22) Anglo Irish B (7) B of Ireland (18)	Allied Irish B (20) Anglo Irish B (9) B of Ireland (8)	Allied Irish B (14) B of Ireland (6)		Allied Irish B (5)
Italy	B Intesa (3) B di Roma (3) BP Milano (6) BDB (6) Sanpaolo IMI (9) Unicredito (7)	B di Roma (6) Rolo Banca (8) Sanpaolo IMI (11) Unicredito (3)	BDB (3) Rolo Banca (4) Sanpaolo IMI (12)	BAM (7) BP Bergamo (7) BPCI. (4) BDB (6) CV (12) Unicredito (3)	BAM (9) B Lombarda (9) BP Bergamo (10) CV (17) BDB (5) Sanpaolo IMI (3)	BAM (6) BP Bergamo (9) BPCI (4) BDB (6) CV (16) Sanpaolo IMI (4)
Netherlands	ING (8)	ING (4)	ING (7)	ABN Amro (3) ING (20)	ABN Amro (13) ING (24)	ABN Amro (7) ING (26)
Portugal	None	BES (7) BPI (7)	BPI (4)	BCP (16) BES (10)	BCP (10) BES (22)	BCP (12) BES (16)
Sweden	None	None	None	None	None	None
United Kingdom	Abbey National (23) B of Scotland (16) Barclays (9) NW (11) HSBC (10)	Abbey National (21) B of Scotland (7) Barclays (9) NW (10) HSBC (8) Stand. Chartered (5) RB of Scotland (16)	Abbey National (31) B of Scotland (15) Barclays (11) NW (12) HSBC (10) RB of Scotland (7)	NW (3) HSBC (14)	None	HSBC (6)

Figure 6.3
Cross-border contagious influence: Germany

A thin arrow means that banks in country A have some contagious influence to at least one bank in country B. A thick arrow means that banks in country A have contagious influence to a bank in country B with within-country systemic importance.

Finally, the data easily lend themselves to the preparation of "contagion charts", in which the links among the banking systems in different countries are graphically represented (Figures 6.3-6.7). We have limited ourselves to showing the map for the largest five European countries. A thin arrow on the figure indicates that there is some contagious influence from the banks in one country to another. A thick arrow indicates that there is some contagious influence from the banks in one country on a bank that was identified as systemically important within its own country in Table 6.12. The figures show how closely linked banking systems of different countries are. For example, the link between German and UK banks seems to be quite strong, as the banks in each country tend to have contagious influence on the systemically important banks in the other. But there are also unidirectional links among countries. Considering the German chart once more, Danish and Irish banks have contagious influence upon German banks, but not vice versa. How should this be interpreted? Clearly the converse of contagious influence as described in this chapter must be some sort of exposure to risks in the other banking system (abstracting from pure contagion). Hence, the thick arrow from Ireland to Germany in Figure 6.3 suggests that German banks are substantially exposed to the Irish banking system. This exposure could manifest itself through direct exposures, i.e. in the money

Figure 6.4
Cross-border contagious influence: France

A thin arrow means that banks in country A have some contagious influence to at least one bank in country B. A thick arrow means that banks in country A have contagious influence to a bank in country B with within-country systemic importance.

Figure 6.5
Cross-border contagious influence: Italy

A thin arrow means that banks in country A have some contagious influence to at least one bank in country B. A thick arrow means that banks in country A have contagious influence to a bank in country B with within-country systemic importance.

Figure 6.6
Cross-border contagious influence: Spain

A thin arrow means that banks in country A have some contagious influence to at least one bank in country B. A thick arrow means that banks in country A have contagious influence to a bank in country B with within-country systemic importance.

Figure 6.7
Cross-border contagious influence: UK

A thin arrow means that banks in country A have some contagious influence to at least one bank in country B. A thick arrow means that banks in country A have contagious influence to a bank in country B with within-country systemic importance.

market, in exposures through the payment system, ownership links and potential direct exposures to non-financial sectors in the country. It would go beyond the scope of this chapter to explore the exact nature of these links, however; rather, we view these maps as a basis for further research into the underlying fundamentals for these links.

6.6 Conclusions

This chapter analyses bank contagion in a sample of 67 EU banks for the period 1991-2003. The methodology employed builds upon previous work on financial market contagion (Bae, Karolyi and Stulz, 2003). First, we analyze the properties of three weekly indicators: the simple first difference of the distance to default (measuring absolute shocks), the log-differenced distance to default (percentage shocks) and, as robustness check, abnormal returns. Monte Carlo simulations show that the patterns observed in the tails of the data, regardless of the measure used, are inconsistent with standard multivariate Normal or student t distributions, suggesting substantial non-linearities. Based on this finding the study proposes a simple non-parametric measure of what is labeled "net contagious influence". We show that this measure may be able to accurately measure contagion among any bank pair, as long as the probabilities of an idiosyncratic shock hitting the two banks are quite similar. We control for differences in these probabilities by adjusting our measure for bank size, arguing that bank size may pick up important differences in the business mix of banks.

We use the measure to identify banks, which have systemic importance within countries and across countries. While the results seem quite sensible for most countries, in Italy and Spain the measure seems to suggest that an unreasonable number of very small banks have systemic importance. We argue that the reason for this uncomfortable finding may be that Italian and Spanish small banks have a particularly low probability of experiencing an idiosyncratic shock and hence our measure overstates contagion of these banks with respect to other banks. Overall, the chapter shows that there may be tight links among banks within countries, as well as links connecting the major banking systems in Europe. We do not detect a major difference between the strength of links among euro area versus non-euro area countries.

We view the chapter as a first step towards devising market based indicators of how vulnerable banks and banking systems may be to contagion. The measure of contagion suggested in this chapter has the advantage of being able to identify the direction of contagious influence among banks, although only on a "net" basis. The results presented in the chapter may provide a basis to obtain a better understanding of the extent to which European banking systems have become interconnected and how banking problems could spread across borders. The study, however, is a purely statistical exercise and to explain the patterns obtained in this chapter with fundamentals remains an important avenue for future research.

6.A. Results from a one factor model

Results from estimating equation (6.5). Dependent variable is the log return of bank *i* in week *t*, the independent variable is the log return of the market portfolio (broad market indices) of country c, in which the bank has its headquarters.

	$\alpha 0$		$\alpha 1$			R-squared
	Coefficient	Standard error	Coefficient	Standard error	T-value	
Bank Austria	0.093	0.187	0.867	0.095	9.135	0.164
Creditanstalt	-0.065	0.172	1.095	0.066	16.687	0.402
KBC Bank	0.078	0.102	1.194	0.045	26.274	0.504
Bankgesellschaft Berlin	-0.249	0.177	0.727	0.066	11.021	0.152
Bayerische Hypo- und Vereinsbank (BHVB)	-0.090	0.138	1.208	0.051	23.474	0.448
BHF-BANK	0.109	0.127	0.563	0.049	11.489	0.168
Commerzbank	-0.148	0.123	1.191	0.046	26.057	0.500
DePfa Group	0.096	0.149	0.601	0.056	10.761	0.158
Deutsche Bank	-0.046	0.100	1.194	0.037	32.197	0.604
Dresdner Bank	0.045	0.119	0.903	0.047	19.231	0.362
IKB Deutsche Industriebank	-0.010	0.086	0.417	0.032	13.099	0.202
Danske Bank	0.068	0.103	0.952	0.045	21.132	0.397
Jyske Bank	0.068	0.110	0.632	0.048	13.193	0.204
Banco Bilbao Vizcaya Argentaria (BBVA)	0.022	0.101	1.337	0.034	38.805	0.689
Banco Espanol de Credito (BES)	-0.249	0.219	0.781	0.075	10.477	0.139
Banco Guipuzcoano (BG)	0.101	0.088	0.221	0.030	7.381	0.074
Banco Pastor	0.131	0.115	0.426	0.039	10.840	0.148
Banco Popular Espanol (BPE)	0.154	0.111	0.821	0.038	21.751	0.411
Banco Santander Central Hispano	-0.016	0.110	1.335	0.038	35.501	0.650
Banco Zaragozano	0.044	0.126	0.465	0.043	10.814	0.147
Okobank	0.046	0.164	0.184	0.034	5.345	0.042
Sampo Leonia	-0.021	0.233	0.581	0.050	11.617	0.166
BNP Paribas	-0.008	0.169	1.209	0.059	20.665	0.470
CPR	-0.139	0.181	0.618	0.071	8.750	0.116
Natexis Banques Populaires	-0.068	0.143	0.659	0.052	12.692	0.192
Societe Generale	0.035	0.141	1.276	0.051	24.916	0.478
Alpha Bank	0.059	0.124	1.024	0.026	40.083	0.703
Commercial Bank of Greece	-0.028	0.156	1.258	0.032	38.989	0.691
Allied Irish Banks	0.052	0.106	1.172	0.041	28.707	0.548
Anglo Irish Bankcorp	0.183	0.147	0.805	0.057	14.231	0.230
Bank of Ireland	0.122	0.102	1.181	0.039	29.910	0.569
Banca Agricola Mantovana (BAM)	0.081	0.104	0.325	0.031	10.408	0.138
Banca Intesa	0.048	0.172	0.998	0.051	19.435	0.357
Banca di Roma	-0.249	0.172	1.203	0.051	23.392	0.446
Banca Lombarda	0.121	0.118	0.342	0.035	9.739	0.123
Banca Popolare di Bergamo	0.063	0.112	0.498	0.033	14.882	0.246
Banca Popolare Commercio e Industria (BPCI)	-0.046	0.133	0.533	0.040	13.347	0.208
Banca Popolare di Intra	0.125	0.118	0.410	0.035	11.596	0.165
Banca Popolare di Lodi	-0.028	0.134	0.502	0.040	12.492	0.187
Banca Popolare di Milano	-0.066	0.150	0.782	0.045	17.438	0.309
Banca Popolare di Verona	-0.018	0.157	0.610	0.047	12.987	0.199
Banco di Desio e della Brianza (BDB)	0.134	0.197	0.455	0.058	7.841	0.133
Banco di Napoli	-0.160	0.311	0.697	0.091	7.638	0.101
Credito Emiliano	-0.068	0.202	0.724	0.061	11.961	0.174
Credito Valtellinese (CV)	0.014	0.100	0.400	0.030	13.425	0.210
Rolo Banca 1473	0.128	0.165	0.763	0.048	15.865	0.307
Sanpaolo IMI	-0.106	0.157	0.986	0.046	21.590	0.454
UniCredito Italiano	0.086	0.151	1.142	0.045	25.315	0.486
ABN AMRO	0.027	0.110	1.259	0.044	28.923	0.565
ING	-0.003	0.110	1.455	0.043	33.668	0.647
Kas-Associatie	0.148	0.141	0.512	0.057	8.990	0.106
Banco Comercial Portugues (BCP)	-0.010	0.104	1.008	0.044	22.723	0.432
Banco Espirito Santo (BES)	0.090	0.112	0.903	0.046	19.688	0.420
Banco Totta e Acores (BTA)	0.080	0.124	0.675	0.053	12.846	0.196
BPI-SGPS	-0.015	0.150	1.259	0.064	19.780	0.366
Skandinaviska Enskilda Banken (SEB)	-0.033	0.259	0.897	0.075	11.979	0.174
Svenska Handelsbanken	0.149	0.190	0.653	0.055	11.936	0.173
Abbey National	0.051	0.136	1.150	0.062	18.592	0.337
Bank of Scotland	0.115	0.154	1.421	0.075	18.995	0.384
Barclays	0.070	0.132	1.423	0.060	23.639	0.451
Close Brothers	0.166	0.159	0.798	0.072	11.018	0.152
National Westminster (NW)	-0.063	0.161	1.531	0.080	19.180	0.415
Schroders	0.103	0.159	1.081	0.072	15.002	0.249
Singer & Friedlander Group	0.060	0.155	0.622	0.071	8.827	0.103
Standard Chartered	0.116	0.164	1.575	0.075	21.079	0.396
HSBC	0.190	0.142	1.487	0.064	23.300	0.498
Royal Bank of Scotland	0.174	0.143	1.445	0.065	22.237	0.421
Average	**0.028**	**0.145**	**0.887**	**0.052**	**18.015**	**0.320**

Chapter 7 Summary and Conclusions

In this thesis we study euro area stock markets and the European banking sector. These markets are especially interesting given the huge number of developments in Europe over the recent past. The history of the European integration process and the changes that can have an impact on asset pricing are briefly described in chapter 1. The remainder of the dissertation shows that the implications of the European integration process clearly stretch to European stock markets. This overall conclusion has immediate consequences for investors in these assets.

Chapter 2 explores the importance of country versus industry factors for investors in euro area stock markets. Most of the literature on this topic shows that country effects have been dominating industry effects in the previous century, both globally as well as in Europe specifically. Rouwenhorst (1999) examines the euro area in detail and finds no changes in the level of country and industry effects in his sample through mid 1998. Other authors, e.g. Cavaglia, Brightman and Aked (2000), Isakov and Sonney (2002) and Adjaouté and Danthine (2001a, 2001b, 2002), find a slow change in the ratio between country over industry effects. We use a mean-variance approach in order to re-examine this issue for the euro area stock markets using a recent sample since 1995. We find that an investor is better off diversifying over different industries compared to diversifying over different countries alone. This conclusion is supported both statistically, by spanning and intersection tests, and visually through plots of mean-variance frontiers. Furthermore, we show that the use of a conditional method leads to the same conclusions as an unconditional method for this sample. We contribute this change to the structural changes in the euro area, since a robustness test on the inclusion of IT-related indices does not result in different conclusions. In other words, the IT-hype around the turn of the millennium did not cause the increase in relative importance of sector factors, but only strengthened the effect found. In line with the research of Cavaglia, Brightman and Aked (2000) and Isakov and Sonney (2002) we expect that this trend is moving on. An important argument is that real integration in the euro area will increase only more as soon as the legal and regulatory barriers between countries will be harmonized even more. For example, these barriers still impede the synergy effects that firms can achieve by clustering industries in the same region.

Chapter 3 concentrates on asset pricing of (portfolios of) assets. The literature in the 80's and 90's has shown that the Capital Asset Pricing Model (CAPM), the base model for asset pricing by Sharpe (1964) and Lintner (1965), does not perfectly explain the returns of portfolios formed by characteristics like size, book-to-market ratio and other ratios. Therefore, Fama and French (1992, 1993, 1995, 1996) introduce a three-factor model (3FM), including a market factor, a size factor and a so-called value factor. Though there is criticism whether these factors really reflect sources of risk, by e.g. Daniel and Titman (1997), the model is very popular amongst both academics and practitioners. This has resulted in a large stream of literature on this model. One of the practical issues concerning the 3FM is whether a local version of the 3FM describes the returns just as good as a global version of the model. Griffin (2002) shows that a local model is better in explaining the cross-section of returns and advocates the use of a local model for Canada, Japan, the U.K, and the U.S. Chapter 3 investigates which 'domestic' model an investor should pursue for the euro area financial markets. Before the introduction of the common currency a local (country) 3FM would intuitively be more appropriate, but this intuition is less strong after the elimination of exchange rate risk on January 1, 1999. We show that the local model has a better performance in our sample from 1991 till 2002. This result holds both when we test a local country 3FM against the euro area 3FM as well as for a local industry 3FM against the euro area 3FM. Apparently, the country or sector information is more important than the euro area wide information that is captured in the bigger model. Furthermore, this conclusion seems to be robust over time as well: the local model outperforms the euro area 3FM. The relative difference between the country 3FM and the euro area version is declining over time, especially for the major countries in the euro area financial markets. We assign this shift to the European integration process. The results in this chapter confirm the conclusions of Chapter 2, stating that the country information is getting less important, while sector information remains an important driver for equity returns.

All attention in chapter 4 is aimed at the role of inflation risk in an international asset-pricing context. Since investors are concerned with asset returns in real terms, uncertainty about inflation is a potentially important source of risk for investors in financial assets. This is especially visible in the euro area. After the elimination of nominal exchange rate risk in the European Monetary Union, inflation differentials between European countries may still imply a non-trivial real exchange rate risk. Angeloni and Ehrmann (2004) document that inflation differentials are still large and persistent also after the launch of the euro. The starting point in this chapter is the International CAPM (ICAPM) of Adler and Dumas (1983). This model has been empirically tested by many papers, starting with Dumas and Solnik (1995) and De Santis and Gérard (1998). Both of these papers assume that the inflation rates are non-stochastic and hence real exchange rate risk collapses to nominal exchange rate risk. We examine the validity of this assumption for the G5-countries: France, Germany, Japan, U.K., and U.S. We find that inflation risk forms a substantial part of the total risk premium for the considered markets in addition to the premium for market risk and nominal exchange rate risk. We find that all risk premia vary over time and that the inflation risk premium is both statistically and economically significant. At the same time we show that the price of inflation risk is much higher than the price of nominal exchange rate risk, implying that investors are more risk averse to bearing one unit of inflation risk than one unit of currency risk. A possible argument for this finding can be found in hedging. It is much easier to hedge nominal exchange rate risk than to hedge inflation rate risk. The market for exchange rate derivatives is very liquid and has been available throughout our sample period, while this is not the case for inflation-linked bonds (the only product that provides a hedge for inflation risk).[87] Lastly, our parameterization provides a natural possibility to test for the validity of the ICAPM. If the ICAPM holds, the prices of risk for nominal exchange rate and inflation risk should be equal. The empirical results strongly reject this hypothesis and therefore do not support the ICAPM.

The second part of this thesis, which embodies Chapters 5 and 6, examines the European banking sector. Chapter 5 studies the level of financial integration between European banks measured by the correlation of bank equity prices. We develop a parsimonious model that is able to detect different integration (correlation) regimes. The model is applied to a set of 41 European banks that have a continuous share price listing over the period January 1990 – March 2003. The main finding in this chapter is that the correlation between larger banks has increased substantially over this period, whereas the correlation between smaller banks has become lower. A reason for this result could be that investors perceive that the activities of bigger banks are becoming more integrated. Another reason may be that as a result of institutional and other larger investors turning their investment strategies towards a European sector-based approach, investors are increasingly tracking indices of the European banking sector. An implication of this

[87] Only the inflation-indexed bond market in the UK has a relatively long history.

phenomenon could be that the European banks will be forced to follow either of two strategies. The first one is to remain a small and specialized bank, with activities in a regional setting. The other strategy is to integrate and become a larger player in Europe. The advantages of the latter strategy are that banks can have easier access to capital markets, leading to lower funding risk, lower costs of capital, and higher credit ratings. As a result capital market forces will help in breaking the integration paradox of European banking.

In chapter 6 we examine the interdependence of bank equity prices during extreme events. Whereas chapter 5 concentrates on the general correlation between European bank stock prices, the interdependence in the tails forms the core of chapter 6. In the first part of chapter 6 we provide evidence for the growing conviction that the tail behavior of bank equity prices is not normally or student-t distributed. Monte Carlo simulations show that the observed frequency of large shocks for European banks cannot be explained by these distributions. Hence, we treat the tail observations of these stocks with a different approach. Following Bae, Karolyi and Stulz (2003) we study the frequency of large shocks through the number of (co-)exceedances. In the second part of this chapter we introduce a non-parametric approach that we label "net-contagious influence". The measure represents the difference in the conditional probabilities of being in the tail between two banks adjusted for differences in the probabilities of being hit by an idiosyncratic shock. We show that this measure should give an accurate indication of contagious influence between two banks. Using this method we identify banks, which appear to have been of systemic importance within individual countries and across countries.

The central theme in this thesis is the question to what extent equity markets have changed over the recent history as a consequence of the European integration process. Clearly, through the introduction of the common currency the exchange rate risk between euro area countries has disappeared, creating a pathway for a higher rate of integration. In this thesis we show with different research methodologies that the consequences of these structural changes are visible at the equity markets. For example, chapter 2 reports that a sector-based approach is more valuable for investors than the more traditional country-based style. Chapters 3 and 5 discuss the consequences for the pricing of (portfolios of) individual stock returns. However, there is still a long way to go. Many differences in legal systems still create obstacles to the full integration of financial markets. For example, the government bond markets show similar yields (there is only a small spread due to differences in default risk of the governments), but the corporate bond markets are also influenced by differences in corporate taxation and tax deductions. This argument holds as well for the equity markets. De Grauwe (2003) states that more progress towards financial integration is essential in order to absorb asymmetric shocks, since the main risk-sharing mechanism that will be available must come from the integration of financial markets. In this thesis we show that equity markets show the first signs of changing behavior caused by the structural changes in the euro area. But, given the necessity for the EMU to harmonize and liberalize financial markets much more, we expect that equity markets will also become more integrated with each other.

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Nederlandse Samenvatting (Summary in Dutch)

In het eerste hoofdstuk staat de motivatie voor dit proefschrift beschreven tezamen met de geschiedenis van het Europese integratieproces en de gevolgen voor het prijzen van aandelen in het algemeen. De rest van dit proefschrift bestaat uit twee delen, die in totaal vijf hoofdstukken beslaan. Het eerste deel (hoofdstukken 2-4) bestudeert de diversificatiemogelijkheden binnen de Eurozone en test verschillende modellen voor het prijzen van aandelen. Deel II (hoofdstukken 5 en 6) concentreert zich op de Europese bankensector, waarbij niet alleen de correlatie (samenhang) tussen de aandelenprijzen van banken wordt bestudeerd, maar ook de bijbehorende risico's ter sprake komen. Hoofdstuk 7 vat de conclusies van dit proefschrift samen.

Hoofdstuk 2 bestudeert de relevantie van landen- en industriefactoren voor het beleggen in het eurogebied. De meeste literatuur van de jaren negentig (en daarvoor) over dit onderwerp vindt dat landeneffecten belangrijker zijn dan industrie-effecten, op zowel globaal als Europees niveau. Rouwenhorst (1999) bestudeert het eurogebied in het bijzonder, aangezien hij wijzigingen voorziet als gevolg van het verdrag van Maastricht uit 1992. Hij vindt echter geen bewijs van structurele wijzigingen en laat zien dat het landeneffect nog dominant is tot halverwege 1998. Meer recente literatuur, zoals Cavaglia, Brightman en Aked (1999), Isakov en Sonney (2002) en Adjaouté en Danthine (2001a, 2001b, 2002), vindt een langzame verandering in de ratio van landeneffecten over sectoreffecten. Omdat de literatuur geen concreet uitsluitsel geeft over de beide effecten, bekijk ik dit onderzoek opnieuw vanuit het perspectief van een investeerder. Hiervoor maak ik gebruik van een andere methodologie (de traditionele portefeuilletheorie van

Markowitz, 1952) en recente data vanaf 1995 van aandelenprijzen uit het eurogebied. Ik laat zien dat een investeerder beter af geweest zou zijn als hij zijn beleggingen gespreid zou hebben over verschillende sectorindices dan over verschillende landenindices. Deze conclusie wordt gebaseerd op een visuele analyse van 'mean-variance frontiers' en statistisch onderbouwd door middel van spanning- en intersectietesten. Het resultaat geldt voor de gehele onderzoeksperiode, maar is sterker na de introductie van de euro per 1 januari 1999. Bovendien toon ik aan dat dit resultaat robuust is en niet wordt veroorzaakt door de IT-hype rond de millenniumwisseling of door verschillen in volatiliteit.

Hoofdstuk 3 concentreert zich op het prijzen van (portfolio's van) aandelen. In de jaren '80 en '90 komt er kritiek op het 'Capital Asset Pricing Model (CAPM)' van Sharpe (1964) en Lintner (1965). Zo blijkt bijvoorbeeld dat het model niet goed werkt voor portfolio's die gevormd worden op basis van karakteristieken als grootte, boek-marktwaarde ratio etc. Fama en French (1992, 1993, 1995, 1996) introduceren daarom een 3-factor model (3FM), waarin een factor voor de markt, een factor voor de grootte en een waardefactor zit. Ondanks het feit dat sommige onderzoekers weer kritiek hebben op het 3FM, omdat de factoren geen werkelijke weerspiegeling van risicofactoren zouden zijn (Daniel en Titman, 1997), is het model toch erg populair onder wetenschappers en beleggers. Dit heeft geresulteerd in een grote stroom aan literatuur over dit model. Eén van de praktische zaken van het 3-factor model (3FM) is de vraag of de lokale versie dan wel de globale versie van het model gebruikt moet worden. Alhoewel het model van origine in principe globaal is, laat Griffin (2002) zien dat het lokale model beter in staat is de aandelen te prijzen voor een steekproef die bestaat uit aandelen van de V.S., Canada, Japan en het Verenigd Koninkrijk. Hoofdstuk 3 onderzoekt welk 'lokaal' model een belegger zou moeten toepassen voor de financiële markten uit het eurogebied. Intuïtief is een "landen-3FM" de meest logische keuze in de periode voor de introductie van de euro, maar na 1 januari 1999 is dit een minder duidelijke zaak. In hoofdstuk 3 komt naar voren dat een lokaal model een betere performance heeft dan een eurowijd model op basis van data van 1991 tot 2002. Dit resultaat blijkt te gelden voor zowel een "landen-3FM" tegenover een "eurogebied-3FM" (welke alleen Europese factoren meeneemt en geen specifieke landenfactoren) als voor een "sector-3FM" (tegenover een "eurogebied-3FM"). Blijkbaar is de land- en industriespecifieke informatie belangrijker dan de globale informatie die in het euro-3FM model zit. Daarnaast blijkt dat de conclusies hetzelfde blijven als de steekproef in twee gelijke delen wordt opgesplitst: het lokale model presteert beter dan het euro 3FM. Wel is het zo, dat de relatieve performance van het landen-3FM afneemt t.o.v. het euro-3FM. Dit laatste blijkt vooral voor de grotere landen van toepassing te zijn (Duitsland, Frankrijk, Italië en Nederland). Deze verschuiving zien wij als gevolg van het Europese integratieproces. De conclusies in dit hoofdstuk bevestigen de resultaten van hoofdstuk 2. Cavaglia, Brightman en Aked (1999) en Isakov en Sonney (2002) rapporteren een stijgende trend in de relatieve waarde van industriële informatie ten opzichte van landeninformatie. De resultaten in de hoofdstukken 2 en 3 laten zien dat deze trend zich daadwerkelijk voortzet en dit effect zal alleen nog maar sterker worden, indien de hervormingen binnen de Europese Unie zich verder voortzetten.

In hoofdstuk 4 is alle aandacht gericht op de rol van inflatierisico bij het prijzen van aandelen in een internationale context. Aangezien investeerders belang hechten aan rendementen in reële termen, kan onzekerheid omtrent de hoogte van de inflatie een belangrijke component zijn voor investeerders bij het bepalen van hun risicopremie. Een concreet voorbeeld hiervan is de huidige situatie in het eurogebied. Na de afschaffing van de wisselkoersen in de Europese Monetaire Unie kan het nog steeds zo zijn dat verschillen in inflatiepercentages tussen eurolanden een zeker reëel wisselkoersrisico met zich meedragen. Angeloni en Ehrmann (2004) laten zien dat de inflatieverschillen tussen eurolanden nog steeds groot zijn na de introductie van de euro. Het uitgangspunt in dit hoofdstuk is het internationale CAPM (ICAPM) van Adler en Dumas (1983). Dit model is empirisch getest door verschillende onderzoekers, waaronder Dumas en Solnik (1995) en De Santis en Gérard (1998). Beide artikelen nemen aan dat inflaties niet-stochastisch zijn en daarmee is het reële wisselkoersrisico gelijk aan het nominale wisselkoersrisico. Hoofdstuk 5 onderzoekt de validiteit van deze aanname voor de G5-landen: Duitsland, Frankrijk, Japan, het Verenigd Koninkrijk en de V.S. en toont aan dat (naast de risicopremie voor de markt en de nominale wisselkoers) inflatierisico een substantieel deel van de totale risicopremie voor de onderzochte markten vormt. Ik laat zien dat alle risicopremies variëren over de tijd en dat de inflatierisicopremie zowel statistisch als economisch significant is. Dit resultaat komt niet voort uit hoge onzekerheid, omdat de volatiliteit van inflatieverschillen niet erg groot is, maar meer door de hoge prijs voor inflatierisico (de risicopremie is het product van de volatiliteit en de prijs voor de betreffende stochast). Dit houdt in dat investeerders grotere risicoaversie hebben voor het hebben van (een eenheid) inflatierisico in hun portefeuille dan voor nominaal wisselkoersrisico. Ons model biedt daarnaast een natuurlijke mogelijkheid om de validiteit van het ICAPM te testen, aangezien de risicoprijzen dan aan elkaar gelijk moeten zijn. De empirische resultaten verwerpen deze test met klem en dus wordt het ICAPM verworpen. De meest logische verklaring voor het feit dat investeerders een grotere mate van risicoaversie vertonen voor inflatierisico dan voor nominaal wisselkoersrisico ligt in het feit dat het hedgen van inflatierisico erg moeilijk is. Voor het afdekken van wisselkoersrisico zijn voldoende liquide instrumenten voorhanden, maar voor inflatierisico zijn er bijna geen. Alleen de inflation-indexed bonds dekken het inflatierisico grotendeels af, maar deze zijn (met uitzondering van het Verenigd Koninkrijk) pas sinds kort op de markt.

Het tweede deel van dit proefschrift concentreert zich op de Europese bankensector. Sinds 1999 is er sprake van een monetaire eenheid voor het eurogebied, waardoor integratie tussen de eurolanden gestimuleerd moet worden - te beginnen met de bankensector. Uit onderzoek blijkt echter dat de bankensector nog voornamelijk nationaal opereert. Zo is bijvoorbeeld het aandeel van buitenlandse banken in een (ander) Europees land kleiner dan 10% (Dermine, 2003). Hoofdstuk 5 bestudeert de financiële integratie tussen Europese banken, gemeten door middel van de correlatie tussen de aandelenprijzen van banken. Wij ontwikkelen een model dat in staat is verschillende 'integratie-regimes' te detecteren. Het model wordt toegepast op een steekproef van 41 Europese banken, die van januari 1990 tot maart 2003 genoteerd staan aan een Europese beurs. De belangrijkste bevinding in dit hoofdstuk is dat de correlatie tussen grote banken significant is toegenomen over deze periode, terwijl de correlatie tussen kleinere banken lager is geworden. Een reden hiervoor zou kunnen zijn dat investeerders denken dat de activiteiten van grotere banken steeds meer overeen komen. Een andere reden zou kunnen zijn dat investeerders steeds meer een Europese bankenindex als *benchmark* gebruiken, omdat institutionele beleggers en andere grote partijen na de invoering van de euro zijn overgegaan op een sectoraanpak (binnen het eurogebied of Europa). De benchmark-indices bestaan voornamelijk uit aandelenprijzen van grotere banken, wat de vraag naar deze aandelen kan verklaren. Dit geeft een nieuwe richting aan de discussie over mogelijke strategieën van banken, welke ook aangestipt worden in dit proefschrift.

In hoofdstuk 6 onderzoek ik de samenhang tussen de aandelenprijzen van banken gedurende extreme situaties. Waar in hoofdstuk 5 de aandacht meer uitgaat naar de correlatie tussen Europese bankaandelen in het algemeen, staat in hoofdstuk 6 de samenhang in de staarten van de verdeling centraal. In het eerste deel van hoofdstuk 6 laat ik zien dat het gedrag in de staarten van de aandelenrendementen van banken niet normaal verdeeld of student-*t* verdeeld is. De Monte Carlo simulaties tonen aan dat het aantal waarnemingen van grote schokken voor Europese banken niet verklaard kan worden door deze verdelingen. Daarom moeten de staarten van een verdeling onafhankelijk onderzocht worden met een andere aanpak. Ik volg daarom de aanpak van Bae, Karolyi en Stulz (2003) om de frequentie van *co-exceedences* (banken die gezamenlijk een grote schok ervaren en dus allemaal in de staart van hun verdeling zitten) te bestuderen. In het tweede deel van dit hoofdstuk introduceer ik een niet-parametrische aanpak, die ik "netto-besmettingsinvloed" noem (met besmetting wordt hier bedoeld dat een bank die in financiële problemen komt, een andere bank met zich meetrekt in financiële onzekerheid). Allereerst wordt er bepaald wat de conditionele kans is dat een bank zich in de staart van zijn verdeling bevindt. De maatstaf wordt vervolgens bepaald door het verschil in de conditionele kans van twee banken te berekenen. Ik laat zien dat deze maatstaf een goede indicatie is van de besmettingsinvloed tussen de twee banken. Met behulp van deze methode identificeer ik banken, wiens financiële stabiliteit belangrijk lijkt te zijn voor het bankensysteem binnen de verschillende landen en tussen de Europese landen.

De rode draad in dit proefschrift is de vraag in hoeverre de aandelenmarkten de afgelopen jaren veranderd zijn als gevolg van het Europese integratieproces. Door de introductie van de gezamenlijke munteenheid is het wisselkoersrisico tussen de landen in het eurogebied verdwenen, wat de weg vrijmaakte voor het vervolg van het integratieproces. In dit proefschrift laat ik met verschillende onderzoeken zien dat de gevolgen van deze structurele veranderingen zeker zichtbaar zijn. Zo blijkt bijvoorbeeld dat het voor beleggers verstandiger is om binnen het eurogebied een sectoraanpak te volgen in plaats van de meer traditionele landenaanpak (hoofdstuk 2). Hoofdstukken 3 en 5 laten zien dat dit ook gevolgen heeft voor het prijzen van individuele aandelen. Er is echter nog steeds een lange weg te gaan voordat de financiële markten volledig geïntegreerd zijn. Verschillen in regelgeving tussen de landen vormen nog immer een obstakel voor het integratieproces. Zo zijn bijvoorbeeld de staatsobligatiemarkten bijna volledig geïntegreerd (er is slechts een kleine spread als gevolg van het verschil in faillissementsrisico). De bedrijfsobligatiemarkt wordt daarentegen ook beïnvloed door verschillen in belastingstelsel en mogelijke aftrekposten. Deze verschillen zijn zelfs nog belangrijker voor aandelenmarkten. De Grauwe (2003) stelt dat het essentieel is om meer voortgang te boeken naar financiële integratie om asymmetrische schokken te kunnen opvangen, omdat het belangrijkste mechanisme om risico te spreiden moet komen van die financiële markten. In dit proefschrift toon ik aan dat de eerste veranderingen op de aandelenmarkten al duidelijk zichtbaar zijn. Ik verwacht dat de integratie van financiële markten nog verder zal toenemen gegeven de noodzaak om regelgeving te harmoniseren en de financiële markten te liberaliseren voor de stabiliteit van de EMU.

Biography

Gerard Moerman (1976) received his Master's degree in Econometrics from the Erasmus University Rotterdam in 1999. In October 1999 he joined ERIM to carry out his doctoral research at the Financial Management department of the RSM Erasmus University. During this time he spent seven months at the European Central Bank (Frankfurt) as an economist at the General Economic Research Department. Some of his work has been published and presented at international conferences. His current research interests include empirical asset pricing, banking and financial integration. Also, he has reviewed several papers, e.g. for the Journal of International Money and Finance and the ECB working paper series. As of February 2005 he joined AEGON Asset Management as Investment Strategist.

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Empirical Studies on Asset Pricing and Banking in the Euro Area

European capital markets have changed dramatically over the last couple of years. Due to the harmonization of monetary and policy rules and the elimination of exchange rate risk (through the introduction of the euro) countries in the European Monetary Union (EMU) are becoming more integrated. In this thesis the author tries to determine the consequences of this integration process for asset pricing in the euro area. The most important conclusion, which is a central theme of the thesis, is that the characteristics of financial markets in the euro area have been changing. In other words, investors and researchers cannot base their expectations on the (long) historical evidence of these markets, because the structural changes have a clear impact on the characteristics of the markets. For example, the author shows that industry information has become more valuable in terms of portfolio diversification benefits than country information, especially after the introduction of the euro, which contrasts with the literature of the 90's. Therefore, investors should change their view in the euro area to a sector-based approach. Most institutional investors, which are the biggest investors in the euro area, have already changed their view into a sector-based approach. As a consequence, euro area portfolio managers are nowadays tracking sector indices instead of country indices. One of the chapters in part II of the thesis shows the implications of that change for the banking sector. Stock returns of big banks have become more correlated, while this is not the case for smaller banks. The author argues that this is not a result of a similar performance or product portfolio of these banks, but is likely the result of the change in perspective of most euro area investors. Next to these topics, the thesis also covers different asset pricing models (Fama and French three factor models for the euro area and an international asset pricing model that provides evidence of a significant risk premium for inflation risk) and an innovative measure for contagion among European banks.

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